SECTORIAL VOLATILITY TRANSMISSION IN STOCK MARKET: EMPIRICAL EVIDENCE FROM DOW JONES INDICES

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ABSTRACT

The objective of the study is to examine the existence of the volatility and its perseverance in different indices of Dow Jones and the spillover effect among these indices. For this purpose, the daily closing prices of the five indices of Dow Jones, have been collected from July 1, 2001 to June 30, 2019. These indices are Consumer goods, Consumer Service, Health Care, Industrial, and Insurance. In order to estimate the results ARMA (1, 1)/ GARCH (1, 1) model has been used in the study. The results show the existence of volatility in the return of all the indices and the spillover effect has been observed among all the indices. The persistence of volatility has been calculated and its existence for the longer period of time has also been observed. The long term relationship among the sectors has been observed by taking the closing values of the each selected sectors.

Key Words: Dow Jones Indices, Volatility, Persistence of Volatility, Spillover Effect, ARMA (1, 1)-GARCH (1, 1)

INTRODUCTION

There is a significant role of a stock market of a country in organizing and directing the investments in different sectors of the economy. The smooth functioning of a stock exchange could be affected by the high degree of volatility; therefore, the study of volatility has always been a topic of interest for researches and financial analysts. Volatility is a statistical tool used to evaluate the extent to which returns on a particular security or market index can fluctuate. It enables the assessment of risk associated with the security and facilitates an understanding of the potential variations that may occur within a brief time-frame. Investors and policymakers are greatly interested in understanding how volatility is transmitted across various international financial markets in the current era of globalization. Economic integration, the growth of stock markets, financial deregulation and liberalization, and the decline in the cost of information and transactions have all contributed to a remarkable degree of correlation between the volatility and returns of stock markets around the world.

In the case of a volatility spillover, one market's shocks are transferred to another. Volatility spillover can have both positive and negative effects, making it a key variable in the study of the transmission mechanism across different financial markets. When markets are well-integrated, shocks in one market will propagate to others in a natural way. It is also argued that shock movements are more significant in interconnected markets than in non-integrated ones. However, at times of crisis, the volatility spillover effect in financial markets increases. Financial market participants need to know how volatility and shocks are transmitted or spilled over[1] across market over time and they should pay particular attention towards the behavior of the equity market indices in order to evaluate the portfolios.

The study of literature reveals that the phenomenon of volatility and its spillover effect has been studied by many financial researchers. For example, Skintzi and Refenes (2006) studied the volatility spillover from the USA bond market to twelve bond market of the Europe. Their study was confined only to calculate the volatility and its transmission from one country's equity market to another country's equity market or the spillover effect of asymmetric information on the different sectors of the equity market of a country. The performance of publicly traded stocks and actively managed portfolios is often measured against stock indices, making them crucial benchmarks for individual investors, mutual fund managers, and institutional investors. However, the transmission of volatility between sectors within the same equity market has received little attention in the literature. This study aims to fill this gap by exploring the transmission of volatility within equity market sectors.

Volatility spillover is a significant topic as it provides the direction and flow of funds in the stock market, which are essential in this capitalist era. Different authors researched volatility spillovers in a diverse context like Cevik et al. (2020) found stock return and oil prices spillover in turkey; Yin et al. (2020) found volatility spillovers in inter-industry in China; Zhang and He (2021) found volatility spillover in real and financial assets globally; Bui et al. (2022) research volatility and spillover in Vietnam; Marobhe and Kansheba (2022) studies the sector-wise volatility spillover in sub-sectors in the USA during COVID-19. However, in the context of the indices of Dow Jones, We find only a study by Endri et al. (2020), but it focuses only on two sectors, while this study used five indices of Dow Jones on larger data sets before the actual Covid-19 impact.

Therefore, the data to check the sectorial volatility transmission has been collected from Dow Jones Indices. It is one of the largest company in the world which provides business and

[1] It is the spread of change in volatility from one market to another.

financial news to the concerned individuals and as well as companies. The Dow Jones stock market indices are designed to provide complete reporting of the USA equity market. Dow Jones Industrial Average is one of the most watched indices, the volatility of which affects all other sectors of the economy. The indices that measure USA equity performance are formed and maintained using an objective and transparent methodology. The primary goal of these indices is to provide reliable and accurate measures of the performance of the equity market. To achieve this goal, the securities in the market are classified into four levels of specificity: 10 broad sector industries, 19 super sectors, 41 sectors, and 114 sub-sectors, with each level becoming progressively more detailed. This classification system enables investors to analyze the performance of the equity market at varying levels of granularity, depending on their specific investment needs and objectives. By the identified knowledge gap, the following research objectives of the study:

- To investigate the volatility persist in different sectors of the equity market.
- To investigate the volatility transmit from one sector to another sector of the equity market.

The significance of the study is that it will help in developing hedging techniques against the risk that arises due to the volatility and its transmission among the sectors of the equity market. The volatility of one sector of the market could be assessed better. This will help the investors to make rational decisions of their investment. This will also support the investors in making diversified portfolio which would in return minimize the risk and maximize the return. This will facilitate local and foreign investors in order to make better investment decisions by examining the volatility transmission effect among different sectors of the equity market. The study will also provide the guide line to the financial managers and the policy makers of financial issues in Pakistan since here the financial markets are also integrate with each other and this study will help in forecasting future sector return volatility.

REVIEW OF LITERATURE

The financial literature has extensively investigated the phenomenon of volatility and its transmission across markets, with particular emphasis on the impact of volatility shocks in an ARCH/GARCH framework. Karmakar and Shukla (2016) conducted a study on the forecasting of volatility due to spillover effects among different sectors of the BSE (India). The authors suggested that accurate volatility forecasting could be achieved by selecting a group of sectors that avoids multicollinearity and by applying the MGARCH framework instead of the univariate model. Nazlioglu et al. (2015) investigated the volatility transmission between conventional equity markets and Dow Jones Islamic stocks, using data from pre-, during-, and post-2008 financial crisis periods. The authors found that the GARCH approach revealed short-term volatility in the equity market before the crisis, and that Islamic markets are not immune to volatility, behaving similarly to conventional equity markets. Oberholzer and Boetticher (2015) examined the volatility spillover between the South African Rand and Johannesburg Stock Indices (JSE / FTSE indices), using daily data collected from January 2002 to September 2014. The authors used the CCC-GARCH (1, 1) model to analyze the spillover effects of returns and shocks in both markets, showing that the Rand was more sensitive to market shocks compared to all share indices of JSE/FTSE.

Azeem et al. (2015) conducted a study on the impact of financial and real assets on the volatility of the KSE 100 Index using data from 2012 to 2013 on a daily basis for both KSE 100 Index and KSE 30 Index. The results of their research indicated that the returns and volatility of KSE 100 Index mostly depended on its internal factors and policies, as well as its own shocks, as evidenced by the results. Additionally, the study found that the volatility of the KSE 100 Index was not influenced by foreign currency returns. Investigation conducted by (Valls & Chulia, 2014) found the volatility spillover effects between currency and stock markets in ten Asian economies from 2003 to 2014. They used the MGARCH model and concluded that there was bidirectional volatility spillover between the stock and currency markets, regardless of the individual country's development level. Efimova and Serletis (2014) examined the spillover effect of price volatility in the USA by using both uni and multi-GARCH models on data from 2001 to 2013. Their research found that the spillovers were unidirectional. Beckmann and Czudaj (2014) studied the volatility transmission in the agricultural sector's future markets by analyzing the future prices of yellow corn, cotton, and soft red wheat. These markets were chosen due to their high trading volume. The study used the GARCHM and VAR model on data from January 2000 to June 2012 and showed that there was a short-term volatility spillover in agricultural future markets.

Guesmi and Fattoum (2014) conducted a study to investigate the dynamic volatility and return transmission between oil-importing and oil-exporting countries. They focused on five oil-importing countries, including Italy, the United States of America, Germany, France, and the Netherlands, and four oil-exporting countries, including the UAE, Venezuela, Saudi Arabia, and Kuwait. They also examined the correlation between stock market oil prices and used the Brent crude oil index, which represents 65% of daily world oil production, as the indicator for oil prices. The study collected data from the Datastream International database and the Federal Reserve Bank of Saint Louis for the period between September 3, 2000, and December 3, 2010. The data included major political and economic events such as the 9/11 terrorist attack, the Russian economic crisis, the second Gulf war, and financial crises in the Asia, Latin America, and Middle East regions. Multivariate GJR-GARCH models were used to analyze the dynamics of volatility transmission, and the results showed that, for exporting countries, the correlation between stock markets and oil prices was higher during three periods: from 2000 to 2001, from 2003 to 2005, and from 2007 to 2008. Natarajan et al. (2014) also conducted a study on mean volatility spillovers between national stock markets using the M-GARCH model. They collected data from the Down Jones Indices for the period between January 2002 and December 2011 and analyzed three markets: Australia, Germany, and the USA. The results showed a significant spillover among the studied markets, particularly from the USA market to Australia and Germany.

Marobhe and Kansheba (2022) applied WCA on the volatility phenomenon in the pandemic situation. The writers divide their timeline into pre-pandemic, first wave, and second wave eras. Persistent high volatility was witnessed except tourism and travel industry which had lower volatility persistence throughout the second wave. During the first pandemic wave, tourism and travel were the key volatility transmitters. The second wave showed dissociation between food and beverage spillovers and other sub sectors. In the same context Agyei et al (2022) find the significant short-term spillover effect between index and its constituents in BRIC and G7 economies. Endri et al. (2020) found that inflation, interest rate are highly and negatively correlated with Dow Jones Industrial Average. Bui, et al. (2022) examined the volatility spillover and volatility contentedness across different financial markets. The authors use the ARMAGARCH technique to estimate the results for the period of 2012-2021. The result of the study revealed that securities, development investment are highly effected by the market volatility, while the construction sector is least effect by this volatility. In the same manner the result also revealed that Vietnamese stock markets exhibited highly level of inter-contentedness among the sectors an this effect increases in pandemic. The authors also found that Plastic, Food and Building materials are the major sources of risk transmission in the market.

Zhang and He (2021) conducted the study to test the spillover effect among the bitcoin market, oil and major stock market around the world. The authors uses the MSV & DCGC techniques to estimates the models. The result reveals that bitcoin has no spillover effect on other markets but on the other hand, oil and gold has direct spillover effect on the stock markets. It was also suggested by the authors that investors should invest in low and medium correlated assets to reduce the investment risk. Erdoğan et al. (2020) investigated the spillover effect between foreign exchange markets and Islamic stock markets in the context of Malaysia, India and Turkey for the period of 2013 to 2019. The authors use different time varying techniques to estimate the spillover effect. The result shows that there is a spillover effect between foreign exchange market and stock market in the context of Turkey only. In the same context, Yin et al. (2020) investigated the volatility spillover effect among sectors in Shanghai Stock Exchange during 2009 to 2018. The authors use the M-GARCH to estimate the results. The authors found that there is highly integrated industry pairs in SSE. The authors also found that there is high spillover effect among the industries during bull market while low spillover effect during bear market. Cevik, et al. (2020) identify spillover effect in the return series of stock markets in the context of Turkey. The authors use different times slots to identify the EGARCH process and estimate the results.

METHODOLOGY

Data and Sample:

The data for the analysis has been collected from the secondary source- the Dow Jones stock exchange[5]. The data of daily prices on Dow Jones Stock Exchange has been collected for the selected sectors from July 1, 2001 to June 30, 2019. Closing prices of each selected sectors has been taken in order to calculate the long term relationship among these sectors.

Methods of Estimation

The volatility in the stock prices and returns reflect the effect of changes incurring in the different sectors of the stock market. This paper is based on the Efficient Market theory which states that the prices of stocks, bonds and all the other types of securities, are fully incorporated with all information at any point of time. Therefore, the volatility in the stock prices and returns reflect the effect of changes incurring in the different sectors of the stock market. In order to find this effect the author has conducted this study on Dow Jones Indices. The basic theme of this study is to find persistence of the volatility in the selected sectors and its spillover effect. Liu and Pan (1997) found return and volatility spillover effects in the United States and the stock markets of Pacific-Basin. The ARMA (1, 1) & GARCH (1, 1) in mean model has been applied in this study in order to estimate the volatility and its transmission amongst the selected sectors. This model is considered the best one in order to find the spillover effects.

The ARCH/GARC model was developed by the Economist Robert F. Engle 1982. The main objective of these models was to check the volatility of the financial markets. The volatility may be positive and negative during the adjacent periods. This phenomenon often occurs in financial markets. This model is the best tool for the analysis of such volatility in the shorter period. For this purpose, Eviews software has been used. For the analysis of data, time series analysis has been done and to check the long-term relationship Co-integration technique has been applied.

The ARMA (1,1)/GARCH (1,1)technique has been used followed by the two equations as:

$$r_{i,t} = \psi_{i,o} + \psi_{i,1} r_{i,1} + \psi_{i,2} V_{i,t} + \psi_{i,3} \varepsilon_{i,t-1} + \varepsilon_{i,t} \text{----------------} 3.1$$

$$V_{i,t} = \beta_{i,0} + \beta_{i,1} V_{i,t-1} + \beta_{i,2} \varepsilon_{i,t-1} \text{------------------------------------} 3.2$$

The equation 3.1 is called the mean equation and the equation 3.2 is called the variance equation. Where

$r_{i,t}$ = the daily return of the selected index i at time t.

$\psi_{i,1} r_{i,1}$ = Auto regressive term w

$\psi_{i,2} V_{i,t}$ = volatility effect means volatility

$\psi_{i,3} \varepsilon_{i,t-1}$ = moving average term

$\varepsilon_{i,t}$ = is the residual which is normally distributed, and time- varying variance

Every stock index return series is demonstrated as an ARCH (1, 1) model in the mean equation to adjust for possible serial correlation in the data.

In the next stage, to find the mean and spillover effect of volatility across the selected indices has been estimated by finding the standardized residual and its square and substituting them into other markets as:

$$r_{i,t} = \psi_{i,0} + \psi_{i,1} r_{i,t-1} + \psi_{j,2} V_{j,t} + \psi_{i,3} \varepsilon_{j,t-1} + \varepsilon_{i,t} \lambda_{i,2} \epsilon_{i,t} + \varepsilon_{i,t} \text{----------------} 3.3$$

$$V_{j,t} = \beta_{i,0} + \beta_{j,1} V_{i,t-1} + \beta_{j,2} \varepsilon 2_{i,t-1} + \gamma_{j,t}\, \epsilon^2_{i,t-1} \text{---------} 3.4$$

Where $e_{i,t}$ is the standardized residual series for capturing the mean and volatility spillover effect from on index to another. To observe the volatility spillover the exogenous variable $e^2_{i,t}$ has been introduced in the equation.

The daily index returns has been calculated as:

Daily Index Return = (Closing Price-Opening price)/Opening price

Results and Discussion

The results of descriptive statistics have been described in the table 4.1 for the daily returns of the selected indices of the equity market from July 1, 2001 to June 30, 2019. The consumer goods returns has lessor value of its standard deviation behaving as less risky. Consumer Service Returns (CSR) and Insurance Returns (ISR) showing positive skewness meaning thereby both have positive returns and all other have negative skewness showing negative returns. The value of Kurtosis is more than 3 in all indices, therefore, the distribution of returns is leptokurtic showing higher peaks

Table 1: Descriptive Statistics for the Selected Indices the Equity Market

	CGR	CSR	HLR	INR	ISR
Mean	0.028784	0.028798	0.019082	0.023048	0.019986
Median	0.024396	0.026126	0.020592	0.027804	0.005472
Maximum	9.281399	11.59628	6.908317	9.637666	10.95587
Minimum	-7.047612	-10.09462	-7.017924	-9.308236	-10.74022
Std. Dev.	0.927652	1.238373	1.040917	1.334835	1.540429
Skewness	-0.061478	0.005982	-0.370537	-0.195333	0.082152
Kurtosis	12.46753	10.79748	7.956105	9.173563	11.91594

Jarque-Bera	14620.28	9915.604	4095.376	6240.466	12968.54
Probability	0.000000	0.000000	0.000000	0.000000	0.000000
Sum Sq. Dev.	3367.290	6000.852	4239.771	6972.120	9285.246
Observations	4647	4647	4647	4647	4647

Figure 1: Cluster volatility

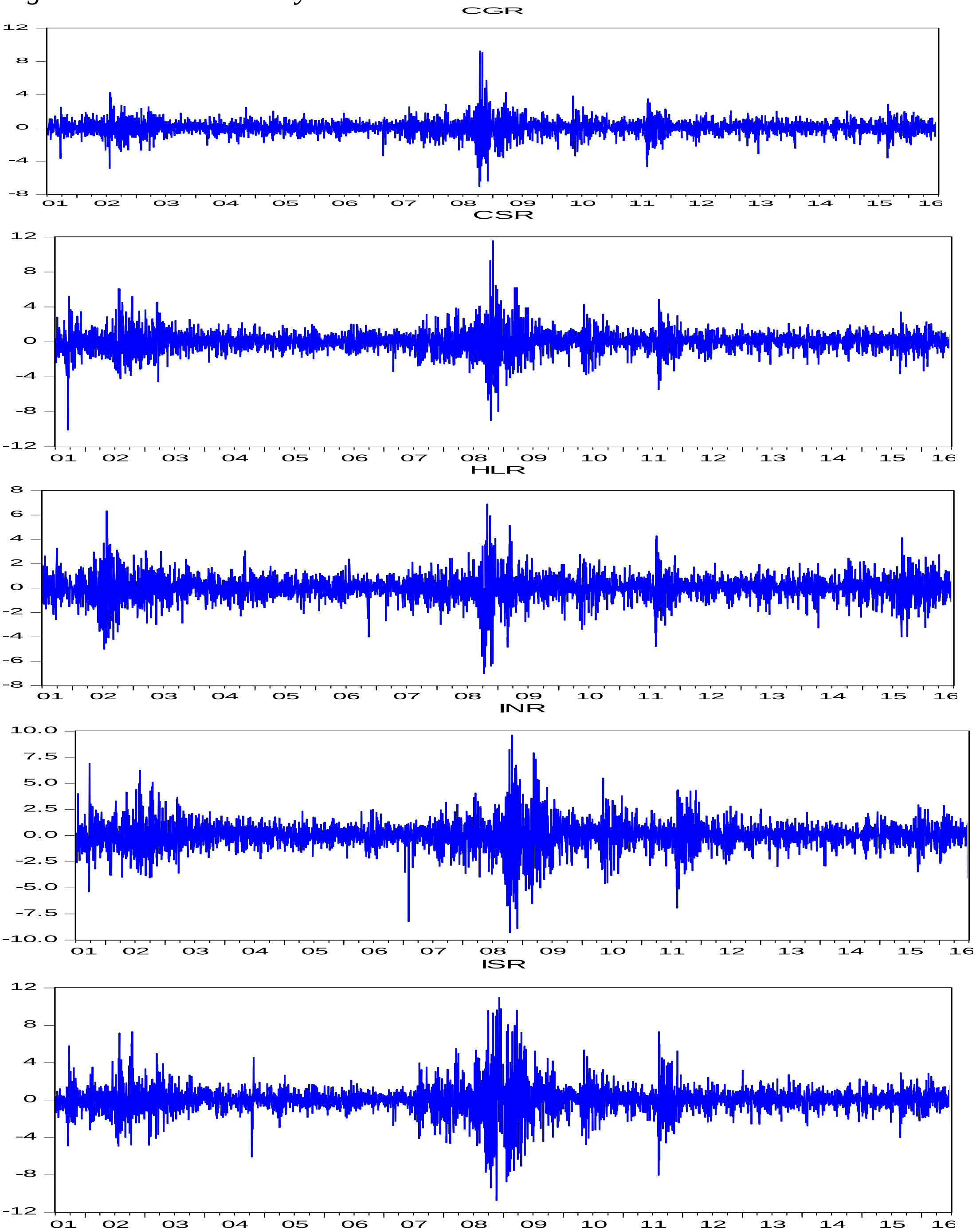

Table 2: Heteroskedasticity Test: ARCH

	CGR	CSR	HLR	INR	ISR
Obs*R-squared	132.4495	106.6045	354.4601	145.0815	504.7363
Chi-Square(1)	0.0000	0.0000	0.0000	0.0000	0.0000

The basic condition of applying the ARCH/GARCH model is that the data should show cluster volatility or conditionally heteroskedastic which is shown by the graph drawn for each index return series. The fig. 4.2 shows that there exists a prolong period of high volatility from 2001 to 2004. It means periods of high volatility is followed by a period of high volatility showing the existence of cluster volatility and for a prolong period of time that is from 2003 to 2008 a low volatility period is followed by a low volatility again showing the cluster volatility. When the data behaves like this, it means that data is conditionally heteroskedastic which satisfies the basic condition for the application of ARCH/GARCH model. In the table 4.2 the results of Heteroskedastic Arch test has been given. Since the P-values in each series is less than 5% so it is significant, therefore, the null hypothesis of no existence of heteroskedasticity cannot be rejected. It means that all the series are conditionally heteroskedastic.

Table 3: Mean and Volatility Spillover Effect Estimation from Consumer Goods Returns to Other Sectors

Particulars	CGR	CSR	HLR	INR	ISR
Ψ	0.057571 0.024444	0.056926 0.020833	0.020006 0.030473	0.035236 0.020668	0.024899 0.015581
ψ_1	0.028610 0.017972	0.059623 0.010227	0.057785 0.012924	0.058347 0.012466	0.051956 0.012299
ψ_2	-0.145206 0.066546	-0.114115 0.034823	-0.106785 0.040086	-0.099328 0.035475	-0.185979 0.032531
ψ_3	0.075449 0.048743	0.093655 0.031377	0.074507 0.034758	0.109535 0.036247	0.139493 0.032464
Λ		0.696249* 0.008336	0.602849* 0.008568	0.751523* 0.010409	0.699559* 0.009444
β_0	0.022311 0.002554	-0.002743 0.001344	0.000200 0.001876	-0.010458 0.001038	-0.004345 0.001876
β_1	0.101934 0.007946	0.087909* 0.007144	0.085238* 0.005639	0.091223* 0.006389	0.081534* 0.005304
β_2	0.866838 0.010319	0.903521* 0.007561	0.901544* 0.006447	0.892633* 0.004980	0.911028* 0.005194
Γ		0.003507* 0.000580	0.003251* 0.000755	0.010650* 0.000500	0.005542* 0.000779
			Residual Diagnostic		
Q(36)	.64	.15	.17	.55	.02
Q(36) Sq	.76	.44	.29	.15	.05
Arch	.36	.92	.21	.62	.04

*Note: * represents the magnitude of significance at 1% level*

The mean and volatility spillover effect has been estimated from CGR (Consumer Goods Return) to CSR (Consumer Service Return), HLR (Health Care Return), INR (Industrial Return), ISR (Insurance Return). The results show the existence of the volatility in CSR because the ARCH and GARCH terms are significant in explaining this volatility at 1% level of significant. The variance regressor 'γ' (CGR) is significant showing the spillover effect from Consumer goods Return to Consumer Service Return which means that shocks in CGR can cause the change in volatility in CSR. The coefficients of mean spillover (0.696249) and variance spillover (0.003507) effects are positive and statistically significant which indicates that CGR and CSR sectors move in the same direction showing the positive spillover effect. As the sum of ARCH and GARCH terms is 0.98 which is closer to one that shows the persistence of volatility for the longer period of time in CSR. The results also show the spillover effect from CGR to HLR. In the same manner, spillover effect is also evident from CGR to INR and ISR. In the residual diagnostics table the P-values have been inserted for each series.

Table 4: Mean and Volatility Spillover Effect Estimation from Consumer Service Returns to Other Sectors

Particulars	**CSR**	**CGR**	**HLR**	**INR**	**ISR**
Ψ	0.045616 0.016700	0.015185 0.053424	0.037975 0.030466	0.045976 0.022277	0.030263 0.015997
Ψ_1	0.022099 0.019930	0.035921 0.066592	0.044427 0.012873	0.054434 0.011231	0.048867 0.012243
Ψ_2	-0.052915 0.054281	-0.134008 0.059998	-0.118436 0.041668	-0.099368 0.034322	-0.163103 0.032150
Ψ_3	0.030053 0.030053	0.075149 0.058575	0.087022 0.035676	0.091549 0.035083	0.105246 0.032305
λ		0.624201* 0.018493	0.597959* 0.008023	0.794907* 0.006578	0.706989* 0.010047
β_0	0.018311 0.002705	0.360843 0.041842	0.006902 0.001949	-0.003322 0.000911	-0.000402 0.002350
β_1	0.088368 0.007471	0.138921* 0.011552	0.108154* 0.007844	0.098992* 0.006333	0.111672* 0.007307
β_2	0.897211 0.008543	0.588763* 0.040263	0.874007* 0.009233	0.890829* 0.004306	0.876319* 0.007064
γ		-0.011712* 0.001283	0.001919** 0.000826	0.007996* 0.000526	0.008475* 0.001285
			Residual Diagnostic		
Q(36)	.35	.24	.23	.34	.45
Q(36) Sq	.41	.35	.47	.80	.98
Arch	.06	.11	.09	.41	.36

*Note: * represents the magnitude of significance at 1% level*
*** represents the magnitude of significance at 5% level*

The mean and volatility spillover effect has been estimated from CSR (Consumer Service Return) to CGR (Consumer Goods Return), HLR (Health Care Return), INR (Industrial Return), ISR (Insurance Return), OGR (Oil & Gas Return), PHR (Pharmaceutical Return). TER (Technology Return), TLR (Telecommunication Return) and ULR (Utility Return) by using ARMA (1, 1) and GARCH (1, 1) mean model. The results show the existence of the volatility in CGR because the ARCH and GARCH terms are significant in explaining this volatility at 1% level of significant. The variance regressor 'γ' (CSR) is significant showing the spillover effect from Consumer Service Return to Consumer Goods Return which means that shocks in CSR can cause the change in volatility in CGR. The coefficients of mean spillover (0.624201) is positive and variance spillover (-0.011712) effect is negative and statistically significant which indicates that CSR and CGR sectors move in the opposite direction showing negative volatility spillover effect. This behavior provides the opportunity to the participants of the equity market to diversify their portfolios. As the sum of ARCH and GARCH terms is 0.71 which is not closer to one showing that volatility does not persist for the longer period of time in CGR. In the residual diagnostics table the P-values have been inserted for each series.

Table 5: Mean and Volatility Spillover Effect Estimation from Health Care Return to Other Sectors

Particulars	**HLR**	**CSR**	**CGR**	**INR**	**ISR**
ψ	0.031368 0.025087	0.029543 0.045126	0.064809 0.029204	0.033084 0.019337	0.021269 0.015053
ψ_1	0.027214 0.021819	0.057889 0.104039	0.040950 0.010865	0.053151 0.014359	0.048083 0.013530
ψ_2	-0.082246 0.063326	-0.076679 0.057323	-0.141907 0.041497	-0.108020 0.039171	-0.151929 0.035168
ψ_3	0.037962 0.053179	0.016728 0.086777	0.073229 0.030589	0.109206 0.040242	0.092827 0.035330
λ		0.687249* 0.028229	0.520908* 0.007486	0.683569* 0.010222	0.631510* 0.009753
β_0	0.023186 0.003212	0.741339 0.131975	-0.002707 0.001256	-0.007734 0.001937	-0.006313 0.002539
β_1	0.094818 0.007825	0.144645* 0.034507	0.087282* 0.006201	0.095348* 0.006403	0.115274* 0.007663
β_2	0.880700 0.009567	0.574871* 0.070169	0.896014* 0.007067	0.893842* 0.005766	0.871650* 0.007743
γ		-0.021045* 0.001481	0.005730* 0.000617	0.011839* 0.001257	0.013394* 0.001297
Residual Diagnostic					
Q(36)	.49	.20	.05	.29	.51
Q(36) Sq	.76	.38	.10	.65	.99
Arch	.37	.18	.06	.58	.95

*Note: * represents the magnitude of significance at 1% level*

The mean and volatility spillover effect has been estimated from HLR (Health Care Return) to CSR (Consumer Service Return), CGR (Consumer Goods Return), INR (Industrial Return), ISR (Insurance Return), OGR (Oil & Gas Return), PHR (Pharmaceutical Return), TER (Technology Return), TLR (Telecommunication Return) and ULR (Utility Return) by using ARMA (1, 1) and GARCH (1, 1) in mean model. The results have been stated in the table 4.5 The results show the existence of the volatility in CSR because the ARCH and GARCH terms are significant in explaining this volatility at 1% level of significant. The variance regressor ‘γ’ (HLR) is significant showing the spillover effect from Health care Return to Consumer Service Return which means that shocks in HLR can cause the change in volatility in CSR. The coefficients of mean spillover (0.687249) is positive and variance spillover (-0.021045) effect is negative and statistically significant which indicates that HLR and CSR sectors move in the opposite direction showing negative volatility spillover effect. This behavior provides the opportunity to the participants of the equity market to diversify their portfolios. As the sum of ARCH and GARCH terms is 0.71 which is not closer to one showing that volatility does not persist for the longer period of time in CSR.

Table 6: Mean and Volatility Spillover Effect Estimation from Industry Returns to Other Sectors

Particulars	INR	CSR	CGR	HLR	ISR
Ψ	0.033192 0.016511	0.073333 0.022202	0.069522 0.029831	0.042144 0.029947	0.027876 0.015974
ψ_1	0.025715 0.022654	0.049711 0.009974	0.044121 0.009015	0.036939 0.013166	0.044820 0.011233
ψ_2	-0.069699 0.056685	-0.117107 0.032462	-0.123103 0.040612	-0.103956 0.041108	-0.161407 0.032416
ψ_3	0.052690 0.054808	0.089805 0.030660	0.068530 0.030168	0.080638 0.036316	0.107761 0.031883
Λ		0.742781* 0.007634	0.582371* 0.006772	0.611057* 0.008792	0.759087* 0.007781
β_0	0.022749 0.002980	-0.001931 0.000811	-0.002616 0.000812	0.002163 0.001983	-0.002970 0.001552
β_1	0.084748 0.006768	0.112302* 0.007780	0.105434* 0.007567	0.127889* 0.008962	0.131408* 0.008151
β_2	0.900518 0.007611	0.877131* 0.007696	0.873220* 0.007210	0.842466* 0.010137	0.856031* 0.007189
Γ		0.007538* 0.000429	0.008643* 0.000496	0.012624* 0.001086	0.014175* 0.000925
Residual Diagnostic					
Q(36)	.30	.42	.61	.29	.39
Q(36) Sq	.51	.79	.99	.69	.79
Arch	.25	.40	.92	.24	.42

*Note: * represents the magnitude of significance at 1% level*

ARMA (1,1) and GARCH (1,1) models were used to estimate the mean and volatility spillover effects from Industrial Return (INR) to various sectors including Consumer Service Return (CSR), Consumer Good Return (CGR), Health Care Return (HLR), Insurance Return (ISR), Oil & Gas Return (OGR), Pharmaceutical Return (PHR), Technology Return (TER), Telecommunication Return (TLR), and Utility Return (ULR). The results, as shown in Table 4.6, indicate that there is volatility in CSR, with significant ARCH and GARCH terms explaining this volatility at the 1% level of significance. The variance regressor 'γ' (INR) is significant, indicating that shocks in INR can cause changes in volatility in CSR. The positive and statistically significant coefficients of mean spillover (0.742781) and variance spillover (0.007538) effects suggest that INR and CSR sectors move in the same direction, showing a positive spillover effect. The sum of ARCH and GARCH terms, which is 0.99, is closer to one, indicating the persistence of volatility in CSR for a longer period of time.

Table 7: Mean and Volatility Spillover Effect from Insurance Returns to Other Sectors

Particulars	ISR	CSR	CGR	HLR	INR
ψ	0.021433 0.012987	0.050907 0.020296	0.043905 0.029388	0.032500 0.028798	0.044989 0.018423
ψ_1	0.043136 0.019193	0.054219 0.011436	0.053751 0.010581	0.047853 0.014103	0.044389 0.011485
ψ_2	-0.160869 0.046240	-0.120236 0.037145	-0.115797 0.043279	-0.121919 0.045553	-0.102050 0.038430
ψ_3	0.109604 0.044855	0.104726 0.034715	0.061827 0.032309	0.091365 0.039122	0.100771 0.038994
λ		0.673250* 0.008577	0.534148* 0.007270	0.559986* 0.008984	0.749214* 0.008857
β_0	0.024078 0.002833	-0.002741 0.001158	-0.000301 0.000998	0.004003 0.002117	-0.001132 0.001730
β_1	0.111188 0.006990	0.087858* 0.007043	0.085199* 0.005440	0.106718* 0.007899	0.134804* 0.011238
β_2	0.877509 0.007079	0.903904* 0.007272	0.901881* 0.005890	0.876205* 0.009735	0.852343* 0.010865
γ		0.006557* 0.000615	0.004450* 0.000464	0.005638* 0.001023	0.011469* 0.000941
Residual Diagnostic					
Q(36)	.38	.41	.47	.53	.61
Q(36) Sq	.87	.77	.93	.82	.98
Arch	.55	.28	.82	.57	.96

*Note: * represents the magnitude of significance at 1% level*

The study estimates the mean and volatility spillover effect between different sectors, including Insurance Return (ISR), Consumer Service Return (CSR), Consumer Goods Return (CGR), Health Care Return (HLR), Industrial Return (INR), Oil & Gas Return (OGR), Pharmaceutical Return (PHR), Technology Return (TER), Telecommunication Return (TLR), and Utility Return (ULR). The analysis employs the ARMA(1,1) and GARCH(1,1) mean model to determine the existence of volatility and spillover effects.The findings reveal that CSR and CGR exhibit significant volatility, as evidenced by the significant ARCH and GARCH terms at a 1% level of significance. The variance regressor 'γ' (ISR) is also significant, indicating the spillover effect from ISR to CSR and CGR, implying that shocks in ISR can cause a change in volatility in these sectors. The coefficients of mean and variance spillover effects between ISR and CSR, as well as ISR and CGR, are positive and statistically significant, suggesting that these sectors move in the same direction, indicating a positive spillover effect. The sum of ARCH and GARCH terms is 0.98, which is closer to one, indicating the persistence of volatility for a longer period in CSR and CGR.

CONCLUSION AND RECOMMENDATIONS

The objective to conduct this study is to find the persistence of volatility in the selected indices and the spillover effect form one sector to another selected sectors in the equity market. Efficient Market theory states that the prices of securities, are fully incorporated with all information at any point of time. Therefore, the volatility in the stock prices and returns reflect the effect of changes incurring in the different sectors of the stock market. In order to find this effect the author has conducted this study on Dow Jones Indices. For this purpose the data has been collected from Dow Jones, the U.S.A based financial company that maintains different indices of the equity market. The time span of the data is from July 1, 2001 to June 30, 2019. These indices are Consumer goods index, Consumer Services index, Health care index, Industrial index, Insurance index. The volatility spillover effect has been calculated by using ARMA (1, 1)/GARCH (1, 1) in mean model. The results has been estimated in the tables starting from table 2 to 7.

In the table 2, the results show persistence of volatility in all the selected sectors of the equity market and in case of CSR, HLR, INR, ISR, the persistence of volatility is for longer period of time. The (CGR) Consumer Goods Returns has the volatility spillover effect to other selected sectors and (INR) shows highest magnitude of this effect. In the table 3, the results show persistence of volatility in all the selected sectors of the equity market and in case of, HLR, INR, ISR, the persistence of volatility is for longer period of time. The (CSR) Consumer Services Returns has the volatility spillover effect to other selected sectors. In the table 5, the results show persistence of volatility in all the selected sectors of the equity market and in case of CGR, INR, ISR, the persistence of volatility is for longer period of time. The (HLR) Health Care Returns has the volatility spillover effect to other selected sectors Thus, the study proves phenomenon of volatility spillover effect and confirms the compliance with the previous studies. The results of the study are consistent with the findings of Koutoms and Booth (1995), they found that there is significant persistence of volatility and existence of spillover effect across New York, Tokyo and London stock markets by using EGRCH model. Same results were found by Ng (2000) who examined the magnitude and changing nature of volatility and found significant spillover effect from Japan and the USA to the six equity markets of Pacific-Basin. Bhar and Nikolova (2007) calculated the mean and volatility spillover effect using regional, world equity and BRIC countries index returns. Mean spillover effect was found by Theodossiou and Lee (1993) whereas short run spillover effect has been found among markets of Greater China region (Johansson & Ljungwall, 2009; Shik, 2004).

Recommendations

It is recommended for all the investors while making an investment decision that they must consider the financial shocks of volatility spillover among the sectors. The results of this study provide the guideline to investors that they should prefer to invest in those sectors which are negatively correlated or spillover effect is negative in order to minimize the risk of their portfolios. In addition to that the results also focus on considering the magnitude of the spillover effect as the sectors having high magnitude effect can adversely impact the performance of the portfolio. Thus, the investors should be vigilant in selecting the sectors portfolio and should analyze the magnitude of the spillover among the sectors. Since in any financial market there occurs the mechanism of volatility and its transmission within the sectors, therefore, the implications of this study also has the application in financial market of Pakistan.

Limitations

There is always a room for the improvements in any research paper, the same case is with this paper. The results of this research thesis can also be improved by observing the following considerations: By adding more variables or sectors from the equity market. This will help in achieving the better results and facilitate investors in having a better diversification for their portfolios. By increasing the time span or increasing the business cycle for the data the results may become more appropriate and reliable so that the trend and phenomenon of the equity markets could easily be understood with improved information and it will help in making rational decision making regarding the investments in the equity markets.

REFERENCES

Azeem, A., Awan, A., Jadoon, A. K., & Sair, S. A. (2015). Impact of financial and real assets on volatility in kse100 index.*Science International*, *27*(1).

Beckmann, J., & Czudaj, R. (2014). Volatility transmission in agricultural futures markets. Economic Modelling, 36, 541-546.

Bhar, R., & Nikolova, B. (2007). Analysis of Mean and Volatility Spillovers Using BRIC Countries, Regional and World Equity Index Returns. *Journal of Economic Integration*, *22*(2), 369-381. Retrieved from http://www.jstor.org/stable/23001101

Efimova, O., & Serletis, A. (2014). Energy markets volatility modelling using GARCH. *Energy Economics*, *43*, 264-273.

Engle, R. (2001). GARCH 101: The use of ARCH/GARCH models in applied econometrics. Journal of economic perspectives, 15(4), 157-168.

Engle, R. F. (1982). Autoregressive conditional heteroscedasticity with estimates of the variance of United Kingdom inflation. *Econometrica: Journal of the Econometric Society*, 987-1007.

Guesmi, K., & Fattoum, S. (2014). Return and volatility transmission between oil prices and oil-exporting and oil-importing countries. Economic Modelling, 38, 305-310.

Johansson, A. C., & Ljungwall, C. (2009). Spillover effects among the Greater China stock markets. World Development, 37(4), 839-851.

Karmakar, M., & Shukla, G. K. (2016). The Effect of Spillover on Volatility Forecasting: An Empirical Study in Indian Stock Market. *Metamorphosis: A Journal of Management Research*, 0972622516629030.

Liu, Y. A., & Pan, M. S. (1997). Mean and volatility spillover effects in the US and Pacific-Basin stock markets.

Malik, F., & Ewing, B. T. (2009). Volatility transmission between oil prices and equity sector returns. International Review of Financial Analysis, 18(3), 95-100.

Mensi, W., Beljid, M., Boubaker, A., & Managi, S. (2013). Correlations and volatility spillovers across commodity and stock markets: Linking energies, food, and gold. Economic Modelling, 32, 15-22.

Mike, S., & Farmer, J. D. (2008). An empirical behavioral model of liquidity and volatility. Journal of Economic Dynamics and Control, 32(1), 200-234.

Natarajan, V. K., Singh, A. R. R., & Priya, N. C. (2014). Examining mean-volatility spillovers across national stock markets. *Journal of Economics Finance and Administrative Science*, *19*(36), 55-62.

Nath Mukherjee, K., & Mishra, R. K. (2010). Stock market integration and volatility spillover: India and its major Asian counterparts. *Research in International Business and Finance*, *24*(2), 235-251.

Nazlioglu, S., Hammoudeh, S., & Gupta, R. (2015). Volatility transmission between Islamic and conventional equity markets: evidence from causality-in-variance test. Applied Economics, 47(46), 4996-5011.

Ng, A. (2000). Volatility spillover effects from Japan and the US to the Pacific–Basin. Journal of international money and finance, 19(2), 207-233.

Oberholzer, N., & von Boetticher, S. T. (2015). Volatility spill-over between the JSE/FTSE indices and the South African Rand. Procedia Economics and Finance, 24, 501-510.

Phillips, P. C., & Perron, P. (1988). Testing for a unit root in time series regression. Biometrika, 75(2), 335-346.

Phume, M. P., & Bonga-Bonga, L. (2018). Return and volatility spillovers between South African and Nigerian equity markets.

Salisu, A. A., & Mobolaji, H. (2013). Modeling returns and volatility transmission between oil price and US–Nigeria exchange rate. Energy Economics, 39, 169-176.

Savva, C. S., Osborn, D. R., & Gill, L. (2009). Spillovers and correlations between US and major European stock markets: the role of the euro. Applied Financial Economics, 19(19), 1595-1604.

Serra, T. (2011). Volatility spillovers between food and energy markets: a semi parametric approach. Energy Economics, 33(6), 1155-1164.

Shik Lee, H. (2004). International transmission of stock market movements: a wavelet analysis. Applied Economics Letters, 11(3), 197-201.

Skintzi, V. D., & Refenes, A. N. (2006). Volatility spillovers and dynamic correlation in European bond markets. Journal of International Financial Markets, Institutions and Money, 16(1), 23-40.

Srivastava, A. (2008). Volatility of Indian stock market: an emperical evidence. *Asia Pacific Business Review*, *4*(4), 53-61.

Tcheunta, J. N., & Tagne, D. R. D. (2017). STOCK MARKETS, VOLATILITY AND ECONOMIC GROWTH. PANORAMA ECONÓMICO, 12(24), 31-31.

Theodossiou, P., & Lee, U. (1993). Mean and volatility spillovers across major national stock markets: Further empirical evidence. Journal of Financial Research, 16(4), 337-350.

Tokat, E., & Tokat, H. A. (2010). Shock and volatility transmission in the futures and spot markets: evidence from Turkish markets. Emerging Markets Finance and Trade, 46(4), 92-104.

Tcheunta, J. N., & Tagne, D. R. D. (2017). STOCK MARKETS, VOLATILITY AND ECONOMIC GROWTH. PANORAMA ECONÓMICO, 12(24), 31-31.

Marobhe, M. I., & Kansheba, J. M. P. (2022). Asymmetric volatility spillover between hospitality sub-sectors during COVID-19: evidence from the USA. Journal of Hospitality and Tourism Insights, (ahead-of-print).

Agyei, S. K., Owusu Junior, P., Bossman, A., Asafo-Adjei, E., Asiamah, O., & Adam, A. M. (2022). Spillovers and contagion between BRIC and G7 markets: New evidence from time-frequency analysis. PLoS One, 17(7), e0271088.

Endri, E., Abidin, Z., Simanjuntak, T. P., & Nurhayati, I. (2020). Indonesian stock market volatility: GARCH model. Montenegrin Journal of Economics, 16(2), 7-17.

Bui, H. Q., Tran, T., Pham, T. T., Nguyen, H. L. P., & Vo, D. H. (2022). Market volatility and spillover across 24 sectors in Vietnam. Cogent Economics & Finance, 10(1), 2122188.

Zhang, J., & He, Q. Z. (2021). Dynamic cross-market volatility spillover based on MSV model: evidence from Bitcoin, Gold, Crude Oil, and stock markets. Complexity, 2021, 1-8.

Erdoğan, S., Gedikli, A., & Çevik, E. İ. (2020). Volatility spillover effects between Islamic stock markets and exchange rates: Evidence from three emerging countries. Borsa Istanbul Review, 20(4), 322-333.

Yin, K., Liu, Z., & Jin, X. (2020). Interindustry volatility spillover effects in China's stock market. Physica A: Statistical Mechanics and its Applications, 539, 122936.

Cevik, N. K., Cevik, E. I., & Dibooglu, S. (2020). Oil prices, stock market returns and volatility spillovers: Evidence from Turkey. Journal of Policy Modeling, 42(3), 597-614.