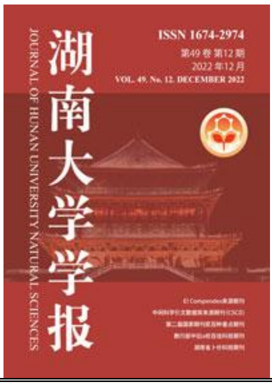

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Evidence of Interdependence between Listed Companies of Major Sector in Dhaka Stock Market

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Abstract: This article focuses on the major companies of different sectors that trade on the Dhaka stock market. In the Dhaka stock exchange, different sectors played a significant role. These sectors have a significant influence on the Dhaka stock market index. Previous research mainly focused on the connection between stock markets and GDP, currency rates, commodities, oil, and so on, but did not focus on the connection between companies inside stock markets. Therefore, it is necessary to estimate the correlation between the companies in various sectors. This article explores the volatility and interrelationships between the companies that can be modeled in DCC-GARCH framework. Concurrently, Diebold and Yilmaz's technique was applied to investigate spillover effects and sector-wise company interconnectedness for robustness purposes. From the sample data, it was observed that the pairwise correlation in the companies is positive and significant. The DCC-GARCH model result revealed that there is evidence of volatility and that it exists over a longer period. The empirical findings indicate significant volatility as well as evidence of interdependence among the listed companies. Dhaka Bank, Aftabauto, RENATA, PRIMETEX, and HRTEX are the most commonly identified shock receivers and transmitters. Diebold and Yilmaz's findings are similar to those obtained using the DCC-GARCH method in that there is an indication of strong interdependence and spillover effects. The findings are essential for micro-investors and the policymakers to make further advancements not only important for a single nation but also for other countries.

Keywords: interdependence, DCC-GARCH model, Dhaka stock market, volatility, the Diebold-Yilmaz method.

达卡证券市场主要行业上市公司相互依赖的证据

摘要：本文重点介绍在达卡股市交易的不同行业的主要公司。在达卡证券交易所，不同的部门发挥了重要作用。这些行业对达卡股市指数有重大影响。以往的研究主要集中在股市与国内生产总值、汇率、商品、石油等之间的联系，而没有关注股市内部公司之间的联系。因此，有必要评估各行业公司之间的相关性。本文探讨了可以在动态条件相关-广义自回归条件异方差框架中建模的公司之间的波动性和相互关系。同时，迪堡和伊尔马兹的技术被用于研究溢出效应和部门间公司的相互关联性，以达到稳健性目的。从样本数据中可以看出，公司之间的成对相关性是显着的正相关。动态条件相关-

广义自回归条件异方差模型结果表明存在波动性的证据，并且存在较长时期。实证结果表明上市公司之间存在显着的波动性以及相互依赖的证据。达卡银行、后备箱、雷纳塔、总理科技有限公司和华润纺织有限公司是最常见的减震器和发射器。迪堡和伊尔马兹的发现与使用动态条件相关-广义自回归条件异方差方法获得的结果相似，因为存在强烈的相互依赖性和溢出效应。这些发现对于微型投资者和决策者取得进一步进展至关重要，不仅对一个国家而且对其他国家也很重要。

关键词：相互依赖、动态条件相关-广义自回归条件异方差模型、达卡股票市场、波动率、迪堡-耶尔马兹方法。

1. Introduction

A country's stock market is a significant part of the economy, uses cutting-edge technology to ensure the highest possible level of trust among stakeholders. Stock exchanges are central to the maximum usage and integration of financial resources to assist economic growth. Bangladesh's stock exchange, which began operations in 1956 and was renamed the Dhaka Stock Exchange (DSE) in 1964, was established for this purpose. The DSE tries improving company performance to increase the trust of stockholders, regulatory bodies, financial institutions, and brokers. Capital markets are linked in ways that are more than simple correlations. These markets have a disproportionate impact on the returns and volatility of other markets [1]. Some stocks are particularly vulnerable as gross receivers of shocks throughout others. The interdependence of capital markets may also change in time and convey inconsistencies during key economic or geopolitical incidents. GARCH types of models, for example, can be used to investigate the dynamic interconnectivity and integration between financial markets [2]. This study especially explores the financial interconnectedness of the sector-wise companies.

In recent times, stock markets, like some of the other capital markets, are becoming more and more integrated. Furthermore, financial markets, especially the stock markets, are volatile because of the uncertain nature of asset returns, which increases the difficulty of risk assessment. Stock returns are considerably more volatile and riskier than those in other financial markets. High volatility results in high risk, whereas low volatility results in lower risk [3]. As a result, it is essential to investigate the relationship between companies belonging to the same category in a stock market. The previous study concentrated on volatility, spillover effects, co-movement, and interconnection between stock and other financial markets, but did not concentrate on interconnection within the market. Financial and trading liberalization, modernization, and technological advancement have all contributed to stronger interconnections. In contrast, increased price volatility and speculation within the stock market have resulted in a medium for the transmitting of risk and returns spillovers throughout various companies [4]. Because the interrelations between different companies have significant ramifications for business analysis techniques, portfolio optimization, and risk evaluation, there is a gap in the literature.

Most research focuses on the interdependence of stock markets with gold, energy markets, commodities markets, exchange rates, GDP, cryptocurrencies, and other financial instruments [5–7]. There has been multiple studies done on stock markets, but no one has focused on the impact of pairwise companies within the sector. This impact had a significant influence on the overall stock index. Our primary goal is to visualize the interrelationship of two companies within a sector. This study is different from the previous literature in the following way (i) this study examines interrelationships between the companies within the sector of a stock market, (ii) the findings cross checked through pairwise correlations of the sample data, DCC-GARCH method, and the Diebold and Yilmaz [8, 9] method. Because of the volatility, unpredictability, and stochastic behavior of stock markets, modeling and forecasting are extremely difficult. The prominent method for modeling volatility is to enable conditional variance, which varies across time due to previous errors, and this approach is parameterized [10]. The DCC-GARCH model is one of the finest methods to detect volatility persistency and the degree of correlation, hence it was employed in this work to capture volatility and correlation. Simultaneously, Diebold and Yilmaz [8, 9] method was employed to investigate spillover effects and connectedness of sectoral companies. This research aimed to uncover volatility persistence, and intercorrelations among companies.

Other sections of this work are divided into materials and methods combined with data description of sample data and a brief discussion of the methods used in this paper. In the results and discussion section, empirical findings and physical implications are thoroughly discussed, and the conclusion section concludes a closing statement.

2. Previous Literature

Volatility movements and the correlation between national and global monetary markets have drawn the attention of financial academics, particularly market specialists, over the last few decades. Therefore, as consequence, an increasing number of research have been conducted to investigate the relationship between national and global monetary markets [11–13]. It is crucially important for market investors to comprehend how volatility and shocks spread across markets over time. Ajmi et al. [14] studied the volatility transmission throughout the international markets considering the period during COVID-19. Their findings show that the interdependence of the inspected markets increased during the COVID-19 pandemic, demonstrating a lack of hedging potential. In comparison to other epidemics, the COVID-19 outbreaks had a significant impact on financial markets, that identifies the intensity of this economic scenario [15]. Maghyereh and Abdoh [16] conducted a study to examine the volatility connections among bitcoin and five conventional monetary assets using both the wavelet coherence method and dynamic frequency-domain. The findings of this study demonstrate a weak or negative correlation before the pandemic and a positive connection during the crisis period. It is important to keep in mind that most studies show positive integration between stock markets and other financial markets. However, the Russia-Ukraine conflict has had a negative economic impact on other nations and the world economy. According to studies, there are negative effects on the share markets, commodity prices, and energy prices [5, 17]. According to Alam et al. [18], this invasion has a significant impact on the stock and commodity markets, and these markets have become shock receivers. The existing literature on the interconnectedness between exchange rates and stock markets, energy and stock markets, commodities and stock markets, and so on is well developed yet diverse, with no consistency.

Previously, several researchers have used time-series models to study the short- and long-term co-movements between stock market returns and other financial markets. For example, Adjasi and Biekpe (2006) investigated the link between the returns of stocks and currency rate co-movements in the African nations. Their findings assume that currency depreciation affects stock returns in the short term while increasing stock market values in some nations in the long term. According to Dahir et al. [20], time-series models used in the past studies do not consider the temporal and multi-scale characteristics and are limited to just short- and long-run periods. According to empirical research, there are differences in the outcomes of equity market co-movements during monetary and non-monetary crises [21, 22]. Several studies confirm that the Global Financial Crisis, European Debt Crisis, COVID-19 epidemic, and Russia-Ukraine war have all had a significant impact on spillover effects, interconnection, co-movements, and so on [18, 23–26].

The financial markets' stability increases their capacity to withstand unforeseen shocks. Volatility in the market has significant ramifications for various macroeconomic characteristics. The interconnection of commodities, foreign currency, and equity markets raises further concerns since volatility in any of these areas can have a knock-on influence on the other markets [27]. Capital markets are a typical sophisticated process with several variables, and econometric models are an effective analytical tool for investigating the interconnectivity of economic factors. Scholars highlight the necessity and utility of econometric modeling techniques in financial research by successfully portraying intangible interconnections in the actual world. According to Ling et al. [28], the interconnection of financial markets is also described using two forms of networks: correlation-based and info spillover networks. Qamruzzaman et al. [29] employed the ARCH-GARCH and granger causality tests to investigate interconnections. They discovered a long-run relationship and the occurrence of volatility persistency in capital markets.

According to past studies, practically all researchers studied stock markets with other assets. They have researched the stock market's spillover effects and hedging or influence on other assets or connectedness with other assets, but no one has focused on volatility dynamics and interlinkages inside sector-wise companies. This research focuses on the influence of major companies in a sector, their interconnections, and volatility persistence.

3. Materials and Methods

3.1. Data Sources

The data of five banks in the banking sector, five companies in the Engineering sector, five companies in the Pharmaceuticals and Chemicals sector, and five companies in the textile sector collected from Investing. com are the daily closing prices of Islami Bank, Dhaka Bank, Bank Asia, Brac Bank, and IFIC Bank; AFTABAUTO, BBSCABLES, BSRMSTEEL, GPHISPAT, and SINGERBD; SQURPHARMA, ACI, IBNSINA, MARICO, and RENATA; PRIMETEX, ALHAJTEX, ENVOYTEX, HRTEX, and STYLECRAFT from 1st January 2018 to 8th June 2022. These are the five major sectors of the Dhaka stock exchange. This sample period contains 1029 observations. The returns are mentioned as dIslami, dDhaka, dAsia, dBrac, and dIFIC; dAFTAB, dBBS, dBSRM, dGPH, and dSINGER; dSQUR, dACI, dIBNSINA, dMARICO, and dRENATA; dPRIME, dALHAJ, dENVOY, dHRTEX, and dSTYLE, respectively. The sample data were not stationary. We used logarithmic return to remove such nonstationary stage. Let logarithmic return r_t, daily-closing price p_t at time *t* and daily closing price p_{t-1} at time *t-1*. Then the logarithmic return for daily closing price are as follows:

$$r_t = 100 * \ln(p_t / p_{t-1}) \tag{1}$$

Table 1 shows that the Augmented Dickey-Fuller (ADF) test for the unit root confirms that the nonstationary condition is removed after taking the logarithmic return.

Table 1 ADF test for unit roots

Bank			**Engineering**		
Variables	Test Statistic	Remarks	Variables	Test Statistic	Remarks
Islami Bank	-1.833	Non-stationary	AFTABAUTO	-2.359	Non-stationary
dIslami	-27.861	Stationary	dAFTAB	-31.749	Stationary
Dhaka Bank	-3.063	Non-stationary	BBSCABLES	-2.266	Non-stationary
dDhaka	-31.919	Stationary	dBBS	-34.117	Stationary
Bank Asia	-3.169	Non-stationary	BSRMSTEEL	-1.325	Non-stationary
dAsia	-30.233	Stationary	dBSRM	-32.207	Stationary
Brac Bank	-2.528	Non-stationary	GPHISPAT	-0.29	Non-stationary
dBrac	-33.080	Stationary	dGPH	-31.51	Stationary
IFIC Bank	-1.442	Non-stationary	SINGERBD	-2.422	Non-stationary
dIFIC	-30.610	Stationary	dSINGER	-32.322	Stationary
Pharmaceuticals and Chemicals			**Textile**		
Variables	Test Statistic	Remarks	Variables	Test Statistic	Remarks
SQURPHARMA	-1.958	Non-stationary	PRIMETEX	-2.131	Non-stationary
dSQUR	-29.25	Stationary	dPRIME	-30.923	Stationary
ACI	-1.823	Non-stationary	ALHAJTEX	-1.092	Non-stationary
dACI	-30.961	Stationary	dALHAJ	-28.751	Stationary
IBNSINA	-2.949	Non-stationary	ENVOYTEX	-1.337	Non-stationary
dIBNSINA	-32.22	Stationary	dENVOY	-32.955	Stationary
MARICO	-0.832	Non-stationary	HRTEX	-0.433	Non-stationary
dMARICO	-29.023	Stationary	dHRTEX	-31.353	Stationary
RENATA	-0.614	Non-stationary	STYLECRAFT	-1.093	Non-stationary
dRENATA	-35.499	Stationary	dSTYLE	-29.31	Stationary

Table 2 displays the descriptive statistics, which show that the mean of some variables is positive while others are negative. In the sample, there is the presence of clustering, which is clearly visible in the variance column. Dhaka Bank and STYLECRAFT's returns are negatively skewed while others' returns are positively skewed, indicating that Dhaka Bank, and STYLECRAFT have a longer left tail while others have a longer right tail. The skewness value of the IFIC bank return is close to zero, implying a symmetric distribution. The kurtosis value of all returns was greater than three, indicating a leptokurtic distribution, indicating heavy tails.

Table 2 Descriptive statistics of five banks in Dhaka stock markets

Sector	**Variables**	**Mean**	**Variance**	**Standard deviation**	**Skewness**	**Kurtosis**
Bank	dIslami	-0.01	2.49224	1.57868	0.90026	10.92729
	dDhaka	-0.02993	3.75688	1.93827	-0.10623	12.72587
	dAsia	-0.0008	2.7525	1.65907	0.11637	7.75383
	dBrac	-0.03457	6.33641	2.51722	0.46407	28.82629
	dIFIC	0.00519	6.38853	2.52755	0.071	17.63173
Engineering	dAFTAB	-0.08243	4.68701	2.16495	1.17868	9.26222
	dBBS	-0.02454	6.12805	2.47549	0.37086	12.77238
	dBSRM	-0.00377	3.49669	1.86994	0.98492	8.65430
	dGPH	0.05925	5.09377	2.25694	0.72288	8.63308
	dSINGER	0.01005	2.42142	1.55609	0.71674	9.47134
Pharmaceuticals and Chemicals	dSQUR	-0.01852	1.58632	1.25949	0.74442	14.50174
	dACI	-0.00927	4.03901	2.00973	0.40294	11.38061
	dIBNSINA	0.02329	2.65973	1.63087	1.23584	10.65967
	dMARICO	0.07654	1.93509	1.39108	0.67489	9.06161
	dRENATA	0.05694	1.14747	1.07120	0.21173	25.57767
Textile	dPRIME	0.00341	9.82531	3.13454	0.90295	6.90838
	dALHAJ	0.01440	12.12569	3.48220	0.22279	4.51492
	dENVOY	0.02173	5.69784	2.38701	0.74587	7.03890
	dHRTEX	0.09648	8.52040	2.91897	0.62539	6.10842
	dSTYLE	-0.09110	18.32212	4.28043	-9.07894	205.16953

The correlation between the sector-wise variables is reported in Table 3. The variables are significantly (* represent at 5% level) positively correlated with each other. Islami and Dhaka bank, and Dhaka and IFIC bank were relatively highly correlated among the banking sector; AFTABAUTO and BBSCABLES, and BSRMSTEEL and GPHISPAT showed relatively high correlation among the Engineering sector; SQURPHARMA and ACI, SQURPHARMA and IBNSINA, and ACI and RENATA were all relatively highly correlated in the Pharmaceuticals and Chemicals sector; PRIMETEX and HRTEX have a relatively high correlation within the Textile sector.

Table 3 Sector-wise correlation between the variables

		dIslami	**dDhaka**	**dAsia**	**dBrac**	**dIFIC**
Bank	dIslami	1.0000				
	dDhaka	0.4342*	1.0000			
	dAsia	0.1946*	0.3464*	1.0000		

	Continuation of Table 3					
	dBrac	0.1470*	0.1825*	0.1146*	1.0000	
	dIFIC	0.3241*	0.4409*	0.1942*	0.2325*	1.0000
		dAFTAB	**dBBS**	**dBSRM**	**dGPH**	**dSINGER**
Engineering	dAFTAB	1.0000				
	dBBS	0.4504*	1.0000			
	dBSRM	0.3959*	0.3121*	1.0000		
	dGPH	0.3919*	0.3511*	0.4378*	1.0000	
	dSINGER	0.2411*	0.2647*	0.2031*	0.1234*	1.0000
		dSQUR	**dACI**	**dIBNSINA**	**dMARICO**	**dRENATA**
Pharmaceuticals &Chemicals	dSQUR	1.0000				
	dACI	0.3050*	1.0000			
	dIBNSINA	0.3188*	0.2187*	1.0000		
	dMARICO	0.1825*	0.1515*	0.1346*	1.0000	
	dRENATA	0.2914*	0.3059*	0.1884*	0.1772*	1.0000
		dPRIME	**dALHAJ**	**dENVOY**	**dHRTEX**	**dSTYLE**
Textile	dPRIME	1.0000				
	dALHAJ	0.2541*	1.0000			
	dENVOY	0.2812*	0.1388*	1.0000		
	dHRTEX	0.5422*	0.2917*	0.2647*	1.0000	
	dSTYLE	0.1869*	0.1699*	0.1349*	0.1545*	1.0000

3.2. Methodology

In this study, two distinct econometric methodologies would be employed to analyze interconnectedness to meet the aims of our study. Firstly, we built the DCC-GARCH models independently for each section-wise company. The DCC-GARCH method was chosen due to the simplicity of univariate GARCH model and the simple univariate models for associations. It can convey time-varying conditional correlations, implying the extent of financial assimilation amongst section-wise companies. Secondly, Diebold and Yilmaz's [8, 9] generalized VAR framework is used. This approach uses rolling window evaluations of variance decompositions forecast error to investigate the net directional of spillover effects for all of the listed companies, along with the quantity of these spillover effects, which can then be assessed throughout the cluster. By using the same methodologies for each company's stock price across a similar time horizon, it can compare the behaviors of these various sectors, determining how individually (or similarly) they react to shocks from one company or organization to another.

GARCH model types have also emerged as a popular option among researchers visualizing volatilities, as the GARCH models are recognized for their simplicity of application, flexibility to analyze a large constantly varying dataset, and govern for conditional heteroscedasticities. This study used the DCC-GARCH model, which is ideally suited to aid the exploration of dynamic conditional correlations across pairs of markets in a network of various parameters that are dynamically connected with each other. The Diebold and Yilmaz [8, 9] methodology, on the other hand, is methodologically prepared to investigate the connectivity and spillovers between such a financial markets network. Diebold and Yilmaz's empirical findings would give further insights into the analysis of each sector, as well as act as a robustness measure to see whether the conclusions from the two separate methodologies are coherent or conflicting. The methodology of this study is depicted in the Figure 1.

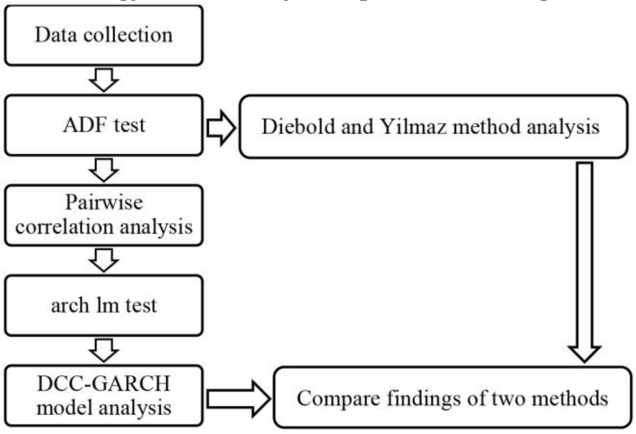

Fig. 1 The flowchart of the research

DCC-GARCH model is an extension of CCC-GARCH of Engle's [30] works by allowing time-varying conditional correlations. To simplify the analysis of wide dimensional systems, elementary DCC-GARCH model assumes that exponential smoothing can describe temporal variation within conditional correlations [30], so that

$$R_t = \mu + \gamma R_{t-1} + \varepsilon_t \tag{3}$$

$$\varepsilon_t = H_t^{\frac{1}{2}} z_t, z_t \sim N(0,1) \tag{4}$$

where returns R_t is $N\times 1$ vectors at time t, conditional mean μ are $N\times 1$ vectors, autoregressive terms γ are $N\times 1$ vectors, error terms ε_t is $N\times 1$ vectors at time t are outlined in equation (4) and the conditional variances and covariances H_t is $N\times N$ matrix. The conditional covariance matrixes H_t specified differently in different types of multivariate GARCH models. The DCC-GARCH model was used for this study because of its capability to describe time-varying conditional correlations, which permitted us to investigate the dynamic flow of volatility spillovers. H_t is specified in the DCC-GARCH model as follows:

$$H_t = D_t^{\frac{1}{2}} R_t D_t^{\frac{1}{2}} \quad (5)$$

$$R_t = diag(Q_t^{-\frac{1}{2}}) Q_t diag(Q_t^{-\frac{1}{2}}) \quad (6)$$

$$Q_t = (1-\alpha-\beta)\bar{Q} + a\varepsilon_{t-1}\varepsilon'_{t-1} + \beta Q_{t-1} \quad (7)$$

The diagonal matrix D_t of conditional variances is denoted by the diagonal coefficients of H_t, whereas Q_t is the nonnegative quasi correlation matrix, with diagonal elements equivalent to 1. The parameters α and β are non-negative scalar, with the constraint that $\alpha + \beta < 1$. When $\alpha = \beta = 0$, then, $Q_t = \bar{Q}$; thus, a constant conditional correlation method would be enough for estimating the correlation matrix. When $\alpha+\beta$ is close to 1, the model would show a high level of persistence in the conditional variance.

Diebold and Yilmaz [8, 9] used the VAR technique including a moving average (MA) element to quantify shock persistence. This MA element is provided by $X_t = \varphi(L) * \varepsilon_t$, where $\varphi(L) = (I - AL)^{-1}$. In addition, denotes Q_t^{-1} the lower triangular Cholesky component of the covariance matrix of ε_t. It is possible to rephrase the aforementioned equation using these formulas as $X_t = \varphi(L) Q_t^{-1} * Q_t \varepsilon_t$. The preceding may be rewritten as $X_t = K(L) * u_t$ by inserting $K(L) = \varphi(L) Q_t^{-1}$ and $u_t = Q_t \varepsilon_t$. For a vector of N variables, assuming a one-step forward prediction given by $\hat{X}_{t+1} = A * X_t$. The aforementioned-predicted error is obtained by $\in_{t+1} = X_{t-1} - \hat{X}_{t+1}$.

$$\in_{t+1,t} = K_0 * u_{t+1} = \begin{bmatrix} a_{1,1} & \cdots & a_{1,N} \\ \vdots & \ddots & \vdots \\ a_{N,1} & \cdots & a_{N,N} \end{bmatrix}_0 \begin{bmatrix} u_{1,t+1} \\ \vdots \\ u_{N,t+1} \end{bmatrix} \quad (8)$$

The coefficients ($a_{i,j}$ where $i \neq j$) can signify how much of the errors can be explained by shocks to other variables, whereas the coefficients ($a_{i,j}$ where $i = j$) describe how much of the errors can be explained by individual shocks. Moreover, since $E(u_t u'_t) = I$, the covariance matrix of $\in_{t+1,t}$ is provided by $E(\in_{t+1,t} \in'_{t+1,t}) = K_0 K'_0$. Consequently, the sum of the entries in the component matrix K_0 is equals to trace of $(K_0 K'_0)$. Thus, the H-step forward total spillover index is calculated as follows:

$$TotalSpilloverIndex = \frac{\sum_{h=0}^{H-1} (\sum_{i,j=1}^{N} a_{h,ij})}{\sum_{h=0}^{H-1} trace(K_h K'_h)} * 100 \quad (9)$$

where $i \neq j$.

Economic interconnectedness is a dynamic term that is anticipated to evolve as time passes and will be influenced by important domestic and international events. To study the dynamic interconnectivity over an extensive period, the elements $a_{i,j}$ indicating the directional flow of spillovers and the overall spillover index might be computed periodically for rolling samples of a particular sample window length. The rolling sample approach employs a certain sample window size, which may be calculated as the time span between the start of the sample and time *t*. This specified period is re-estimated with lag H, which corresponds to the prediction horizon. This is known as H-step forward forecast, and it is calculated recurrently for the same sample window sizes chosen at a predetermined lag H.

4. Results and Discussion

The test statistics of the Breusch-Pagan test for heteroskedasticity are 27.54 with a p-value 0.0000 in the banking sector; 105.08 with a p-value 0.0000 in the Engineering sector; 16.18 with a p-value 0.0001 in the Pharmaceuticals and Chemicals sector; 5.22 with a p-value 0.0223 in the Textile sector and the test statistics of Cameron and Trivedi's decomposition are 52.53 with a p-value 0.0000 in the banking sector; 84.91 with a p-value 0.0000 in the engineering sector; 267.35 with a p-value 0.0000 in the Pharmaceuticals and Chemicals sector; 28.5 with a p-value 0.0122 in the Textile sector implying that the confirmation of heteroskedastic noise. The Lagrange Multiplier (LM) test for ARCH with test statistics is 80.201 and p-value 0.0000 in the banking sector; 48.545 and p-value 0.0000 in the Engineering sector; 78.619 and p-value 0.0000 in the Pharmaceuticals and Chemicals sector; 17.223 and p-value 0.0000 in the Textile sector indicates that the alternative hypothesis is true, i. e., the ARCH effect exists. Since it has been proved that there is the presence of heteroskedastic noise and the existence of the ARCH effect, we can unboundedly employ GARCH family models.

4.1. Experimental Outcomes from the DCC-GARCH Model

The estimated results of DCC-GARCH(1,1) model are reported in Table 4. The coefficients of arch and garch terms are statistically significant at the 1% level except garch term in the banking sector. The fact that the sum of the arch and garch parameters is less than 1 indicates that volatility will continue to be long. Except for the garch term in the instance of the Brac bank, all coefficients are positive. The impact of negative shock persistence indicates that investors prefer a negative influence over a positive influence. The arch coefficient is greater than 0.1, suggesting that the market is jumpy [31]. Residuals plot and variance plot of DCC-GARCH(1,1) model are shown in Figures 2 and 3 respectively. Between the 1st of January 2018 and the middle of 2019, as well as late 2019 and the middle of 2020, there is evidence of significant clustering, which is followed by moderate volatility toward the end. That is, the conditional correlation is clearly highly inconsistent over time. The volatility was fairly high between late 2019 and the middle of 2020, as shown in the variance plot.

Table 4 Estimated results from DCC-GARCH(1,1) model (standard errors in parentheses)

Panel A: Coefficient of arch and garch terms estimated from DCC-GARCH(1,1) model						
	Variables	**dIslami**	**dDhaka**	**dAsia**	**dBrac**	**dIFIC**
Bank	α_1	0.252*** (0.0523)	0.212*** (0.0362)	0.33*** (0.0548)	0.325*** (0.0499)	0.322*** (0.0585)
	β_1	0.647*** (0.057)	0.564*** (0.0585)	0.479*** (0.0852)	-0.0178 (0.0166)	0.47*** (0.0798)
	Variables	**dAFTAB**	**dBBS**	**dBSRM**	**dGPH**	**dSINGER**
Engineering	α_1	0.224*** (0.0395)	0.116*** (0.0271)	0.134*** (0.0223)	0.085*** (0.0242)	0.233*** (0.0325)
	β_1	0.642*** (0.0612)	0.861*** (0.0335)	0.826*** (0.0252)	0.769*** (0.083)	0.764*** (0.0235)
	Variables	**dSQUR**	**dACI**	**dIBNSINA**	**dMARICO**	**dRENATA**
Pharmaceuticals and	α_1	0.186*** (0.0332)	0.231*** (0.0421)	0.277*** (0.0437)	0.641*** (0.0907)	0.209*** (0.0461)
Chemicals	β_1	0.733*** (0.0335)	0.365*** (0.0825)	0.685*** (0.0402)	0.487*** (0.0506)	0.525*** (0.0959)
	Variables	**dPRIME**	**dALHAJ**	**dENVOY**	**dHRTEX**	**dSTYLE**
Textile	α_1	0.19*** (0.03)	0.131*** (0.0232)	0.179*** (0.0323)	0.116*** (0.0234)	0.231*** (0.169)
	β_1	0.727*** (0.0377)	0.824*** (0.027)	0.773*** (0.0381)	0.776*** (0.0473)	0.628*** (0.0212)
Panel B: Correlation between variables estimated from DCC-GARCH(1,1) model						
Bank	corr(dIslam, dDhaka)	corr(dIslami, dAsia)	corr(dIslami,, dBrac)	corr(dIslami, dIFIC)	corr(dDhaka, dAsia)	corr(dDhaka, dBrac)
	0.372*** (0.0438)	0.22*** (0.049)	0.118** (0.0536)	0.247*** (0.0488)	0.357*** (0.0458)	0.178*** (0.0516)
	corr(dDhaka, dIFIC)	corr(dAsia, dBrac)	corr(dAsia, dIFIC)	corr(dBrac, dIFIC)	lambda1	lambda2
	0.403*** (0.0427)	0.153*** (0.0525)	0.186*** (0.0488)	0.155*** (0.0493)	0.0175*** (0.00333)	0.953*** (0.00779)
Engineering	corr(dAFTAB, dBBS)	corr(dAFTAB, dBSRM)	corr(dAFTAB, dGPH)	corr(dAFTAB, dSINGER)	corr(dBBS, dBSRM)	corr(dBBS, dGPH)
	0.431*** (0.0334)	0.348*** (0.0363)	0.338*** (0.0364)	0.217*** (0.0393)	0.304*** (0.0375)	0.326*** (0.037)
	corr(dBBS, dSINGER)	corr(dBSRM, dGPH)	corr(dBSRM, dSINGER)	corr(dGPH, dSINGER)	lambda1	lambda2
	0.171*** (0.0408)	0.387*** (0.0354)	0.167*** (0.0409)	0.0883** (0.0407)	0.0181*** (0.00534)	0.924*** (0.0326)
Pharmaceuticals and	corr(dSQUR, dACI)	corr(dSQUR, dIBNSINA)	corr(dSQUR, dMARICO)	corr(dSQUR, dRENATA)	corr(dACI dIBNSINA)	corr(dACI dMARICO)
Chemicals	0.286*** (0.0315)	0.257*** (0.0327)	0.187*** (0.0337)	0.229*** (0.0339)	0.2*** (0.0331)	0.124*** (0.0341)
	corr(dACI, dRENATA)	corr(dIBNSINA,dMARICO)	corr(dIBNSINA,dRENATA)	corr(dMARICO,dRENATA)	lambda1	lambda2
	0.264*** (0.0318)	0.124*** (0.0344)	0.141*** (0.0341)	0.169*** (0.0338)	0.0422*** (0.0109)	0.644*** (0.0832)
Textile	corr(dPRIME,dALHAJ)	corr(dPRIME, dENVOY)	corr(dPRIME, dHRTEX)	corr(dPRIME,dSTYLE)	corr(dALHAJ,dENVOY)	corr(dALHAJ,dHRTEX)
	0.25*** (0.0398)	0.254*** (0.0399)	0.518*** (0.0319)	0.177*** (0.0428)	0.133*** (0.0415)	0.282*** (0.0394)
	corr(dALHAJ,dSTYLE)	corr(dENVOY,dHRTEX)	corr(dENVOY,dSTYLE)	corr(dHRTEX,dSTYLE)	lambda1	lambda2
	0.151*** (0.0414)	0.225*** (0.0405)	0.151***(0.0436)	0.151*** (0.042)	0.0211*** (0.00518)	0.921*** (0.0231)

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

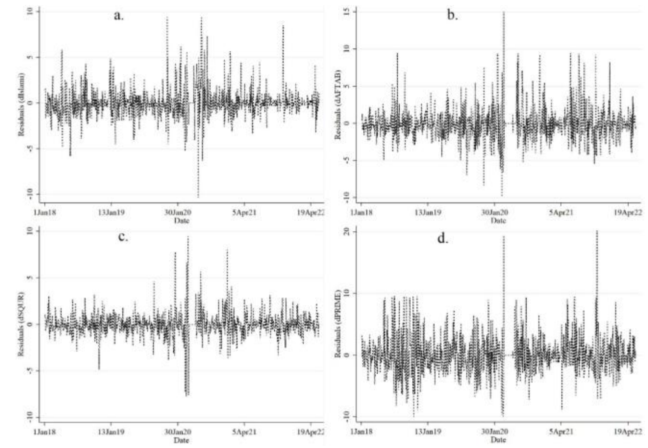

Fig. 2 Part one: Residuals plot for a) banking sector; b) engineering sector; c) pharmaceuticals and chemicals sectors; d) textile sector

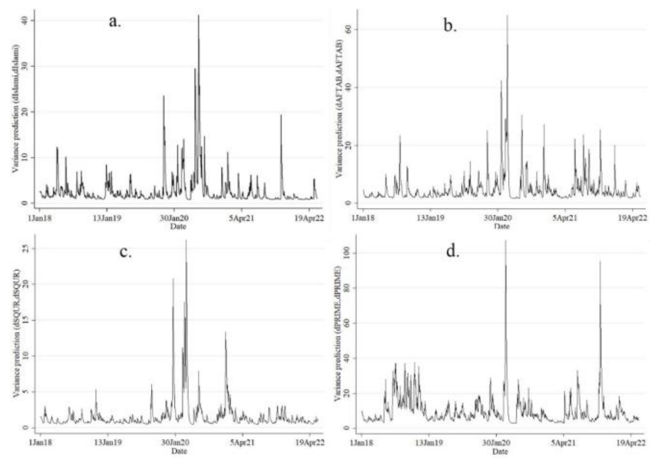

Fig. 3 Part two: Variance plot for a) banking sector, b) engineering sector, c) pharmaceuticals and chemicals sectors; d) textile sector

The variables are significantly positively correlated with each other, as can be seen in Table 4 Panel B. The findings are strikingly similar to the primary findings obtained from sample data analysis in Table 3, where the correlation between the variables is positive. That is the evidence of interlinkage between the sector-wise companies (This is similar to the findings of Yousuf and Zhai [6], who discovered a strong linkage between equity markets and crude oil). Within a sector, one company can influence the price increase or decrease of another company. The fact that the variables are weakly associated shows that the variables have a modest level of interdependence. A relatively strong correlation exists between Islami and Dhaka bank, Dhaka bank and Bank Asia, and Dhaka and IFIC bank in the banking sector, AFTABAUTO and BBSCABLES, and BSRMSTEEL and GPHISPAT in the Engineering sector, SQURPHARMA and ACI, and ACI and RENATA in the Pharmaceuticals and Chemicals sector, and PRIMETEX and HRTEX in the Textile sector, which is analogous to the primary results in Table 3. The adjusted lambdas values are statistically significant, indicating a positive relationship between the variables. Therefore, the relationships remain stable over time. The computed lambdas provide strong empirical evidence of a conditional correlation that changes over time. The sum of lambdas is quite close to one, suggesting a significant level of persistent volatility.

The estimated findings of the DCC-GARCH model that explored the dynamic conditional correlations offered surprising insights about the companies' market integration. Figure 4 demonstrates the dynamic conditional correlations over the study's timeframe among each of the ten probable pairs of the five financial time-series data of a sector analyzed. Higher numbers indicate a high level of financial interconnectedness among companies, and vice versa. The company's correlation was poor at the beginning of the sample. However, after a few months at the start of the sample, an increasing trend in the company's integration level was observed. Furthermore, the association between Islami and Dhaka bank, as well as Dhaka and IFIC bank, s has been relatively strong (surpasses 40% on average) throughout the last several years. This might be due to many common causes, such as a strong banking system, increased client trust, and improved security breeze. While the conditional correlations between AFTABAUTO and BBSCABLES, as well as BSRMSTEEL and GPHISPAT, surpass 40%, the conditional correlations between SQURPHARMA and ACI, as well as ACI and RENATA, stand near 30%. Surprisingly, the dynamic conditional correlations between PRIMETEX and HRTEX stay above 50% for a large portion of the period of this investigation, while the other stays below 30%. This might be attributed to a gap in this sector since trade equity investors are more attractive between PRIMETEX and HRTEX, restricting trading opportunities and impeding diversification because of the high association between these two companies.

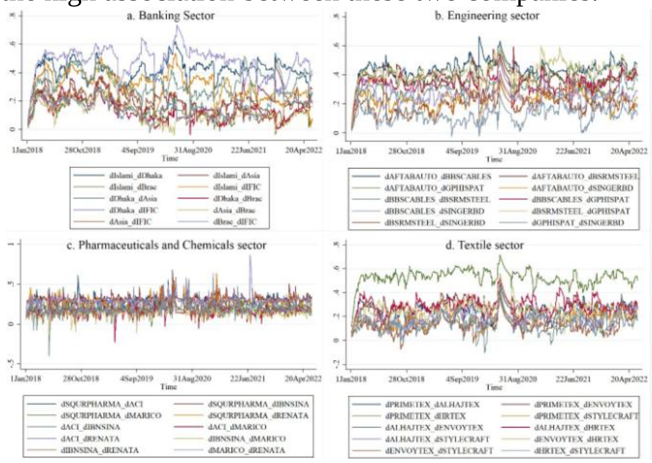

Fig. 4 The graphs above depict pairwise dynamic conditional correlations estimated from DCC-GARCH model and displayed independently for each listed company in a sector of the Dhaka stock market

4.2. Experimental Outcomes from the Diebold-Yilmaz Methods

The connectivity technique developed by Diebold and Yilmaz assists in capturing the change of the spillover index across time. Therefore, this study illustrates how return connectedness and network connection maps examine the direction, strength, and pattern of information spillover across listed companies in a sector. Table 5 illustrates the approximate amount of the correlation of anticipated returns and demonstrates that Islami and Dhaka banks receive the greatest return spillovers, while Dhaka and Brac banks transmit the most. In the case of Engineering sector, AFTABAUTO was the most receiver with 27.81% and a transmitter with 30.26%; RENATA was the most receiver with 22.82% and transmitter with 23.69% for Pharmaceuticals and Chemicals sector; PRIMETEX and HRTEX are the most receivers and transmitter for Textile sector. Also, the total correlation score for all sectors is about 22%, indicating the magnitude of return spillovers in this research framework. Figure 4 displays connections among the five companies of Banking, Engineering, Pharmaceuticals and Chemicals, and Textile sectors, with Brac Bank demonstrating significant connectedness across the system in the banking sector. In the engineering sector, AFTABAUTO and BBSCABLES exhibit high connection all over the system; in the Pharmaceuticals and Chemicals sector, only ACI shows extremely poor connectivity all over the system; and in the Textile sector, PRIMETEX and HRTEX show strong connectivity all over the system, which is comparable to Gabauer [18, 32].

The amount of connectivity might be determined by comparing the present shocks in the overall dynamic connectedness score to past shocks (shown in Figure 4). Figure 4 shows that the last several years have seen waves of uncertainty, which may be related to various regional factors, such as political instability and the COVID-19 epidemic. The connectivity index rises sharply because of the epidemic between the final half of 2020 and the last half of 2021, while equities markets experience volatility. Because of this event, which was preceded by and followed by an economic meltdown, a worldwide financial contagion arose at the same time. It is conceivable that the direction and strength of spillovers change dramatically over time. Therefore, Figure 5 displays individual sector-wise listed company's dynamic graphs of net total directional connectivity. When the value is greater than zero, the company considers itself a net transmitter of shocks to others for that time, whereas when the value is less than zero, the company considers itself a net receiver of shocks from others. Only Brac bank and HRTEX transmit shocks to others most of the time, whereas Islami bank, Bank Asia, SingerBD, ACI, Al-hajtex, and ENVOYTEX receive shocks from others and the rest of the companies fluctuate over time. Brac bank is a high sender of shocks to others, whereas Islami bank is a highly receiver of shocks from others. To investigate the pairwise association between the companies analyzed to develop dynamic net pairwise connectivity graphs for each of the 10 probable pairs of the Dhaka stock market's four major sectors shown in Figures 6 and 7. Brac bank is the net transmitter of shocks to IFIC bank, whereas Islami and Dhaka bank are the net receivers of shocks from Brac bank. While the remaining pairings in the banking sector are very close to zero, this indicates that no shocks are transmitted or received from each other. In the engineering sector, each pairing value near zero indicates relatively weak shocks transmitted and received from each other, except AFTABAUTO, which transmits shocks to BSRMSTEEL over a long time. SQUREPHARMA transmit the highest shocks to IBNSINA, whereas IBNSINA and RENATA transmit the highest shocks to ACI over a longer time. Similarly, PRIMETEX transfers the most shocks to AL-HAJTEX and ENVOYTEX. The remaining companies in the Pharmaceuticals, Chemicals, and Textile sectors, on the other hand, evolve around zero, transmitting and receiving shocks from each other.

Micro-investors might benefit from studying the flow of spillovers across listed companies by sector, as these companies are more likely to be interconnected by sector. For micro-investors, the DCC-GARCH models show strong conditional correlations with Islami and Dhaka bank, Dhaka bank and Bank Asia, Dhaka and IFIC, AFTABAUTO and BBSCABLES, BSRMSTEEL and GPHISPAT, SQURPHARMA and ACI, ACI and RENATA, and PRIMETEX and HRTEX, indicating a potential inflow of spillovers even if there is economic contagion. The findings of the directional interconnectedness derived using the Diebold and Yilmaz [9] technique have revealed which of the sector-wise companies may be the generator of these spillovers. The volatility plot predicted using the DCC-GARCH model, as well as the results of the Diebold and Yilmaz technique, accord with the influence of the COVID-19 pandemic. Thus, the findings of this study might help micro-investors and policymakers respond to shocks that occur in a sector more quickly by forecasting how these shocks would propagate throughout the companies in that sector.

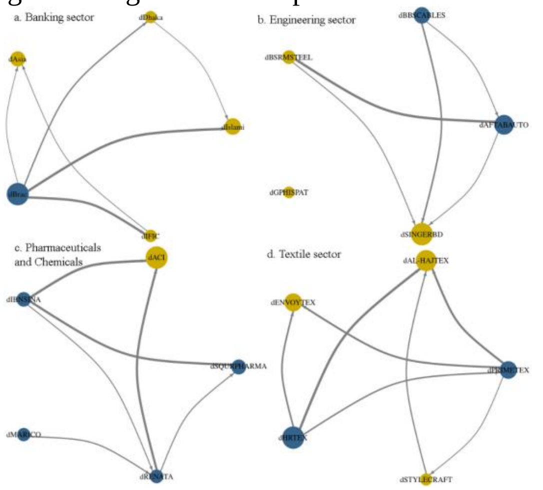

Fig. 5 Total net direction of spillovers among listed companies within the sector using the Diebold and Yilmaz method. The net flow of spillovers is indicated by arrows. The magnitude of the bilateral spillovers is represented by the width of the arrow, the amount of the spillover impact is represented by the size of the junction, and the color indicates whether a company is a net transmitter (blue) or receiver (yellow) of spillovers

Table 5 Volatility spillover estimated from the Diebold-Yilmaz methods

Bank		**dIslami**	**dDhaka**	**dAsia**	**dBrac**	**dIFIC**	**FROM**
	dIslami	72.21	8.8	3.12	8.85	7.02	27.79
	dDhaka	7.08	70.42	5.79	7.2	9.52	29.58
	dAsia	3.95	7.17	80.04	4.84	4	19.96
	dBrac	2.73	3.7	3.04	88.12	2.41	11.88
	dIFIC	5.88	8.51	2.03	8.23	75.34	24.66
	TO	19.64	28.19	13.99	29.11	22.94	113.88
	Inc. Own	91.85	98.61	94.03	117.23	98.29	cTCI/TCI
	NET	-8.15	-1.39	-5.97	17.23	-1.71	28.47/22.78
Engineering		**dAFTAB**	**dBBS**	**dBSRM**	**dGPH**	**dSINGER**	**FROM**
	dAFTAB	72.19	10.33	6.78	6.01	4.69	27.81
	dBBS	9.62	76.73	5.65	4.09	3.9	23.27
	dBSRM	8.78	5.24	76.48	6.16	3.35	23.52
	dGPH	6.46	3.98	6.29	80.81	2.47	19.19
	dSINGER	5.4	5.22	4.12	2.88	82.38	17.62
	TO	30.26	24.77	22.84	19.14	14.41	111.42
	Inc. Own	102.45	101.5	99.32	99.94	96.79	cTCI/TCI
	NET	2.45	1.5	-0.68	-0.06	-3.21	27.85/22.28
Pharmaceuticals & Chemicals		**dSQUR**	**dACI**	**dIBNSINA**	**dMARICO**	**dRENATA**	**FROM**
	dSQUR	80.05	3.29	6.14	3.83	6.69	19.95
	dACI	3.55	80.07	4.28	2.71	9.39	19.93
	dIBNSINA	7.93	2.35	81.51	4.82	3.38	18.49
	dMARICO	4	2.49	5.11	84.17	4.23	15.83
	dRENATA	5.82	7.6	4.18	5.21	77.18	22.82
	TO	21.3	15.74	19.7	16.58	23.69	97.02
	Inc. Own	101.35	95.81	101.21	100.75	100.87	cTCI/TCI
	NET	1.35	-4.19	1.21	0.75	0.87	24.25/19.4
Textile		**dPRIME**	**dALHAJ**	**dENVOY**	**dHRTEX**	**dSTYLE**	**FROM**
	dPRIME	72.25	3.23	5.7	14.74	4.08	27.75
	dALHAJ	5.67	80.12	2.63	6.29	5.29	19.88
	dENVOY	7.9	3.12	78.44	7.57	2.98	21.56
	dHRTEX	13.03	3.49	5.66	74.55	3.27	25.45
	dSTYLE	5.1	3.84	3.37	3.85	83.84	16.16
	TO	31.7	13.68	17.36	32.45	15.63	110.81
	Inc. Own	103.95	93.8	95.79	106.99	99.46	cTCI/TCI
	NET	3.95	-6.2	-4.21	6.99	-0.54	27.7/22.16

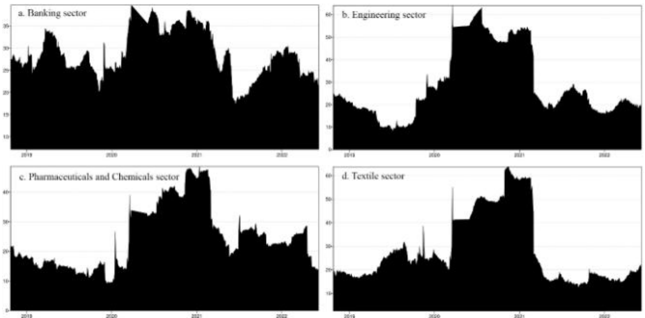

Fig. 6 The overall dynamic connectivity among listed companies in a sector as calculated by the Diebold and Yilmaz method. The quantities might be understood as the proportion of shocks to companies throughout the price cluster under investigation, which can be illustrated by spillovers from other companies throughout the cluster, thus showing the extent of financial integration

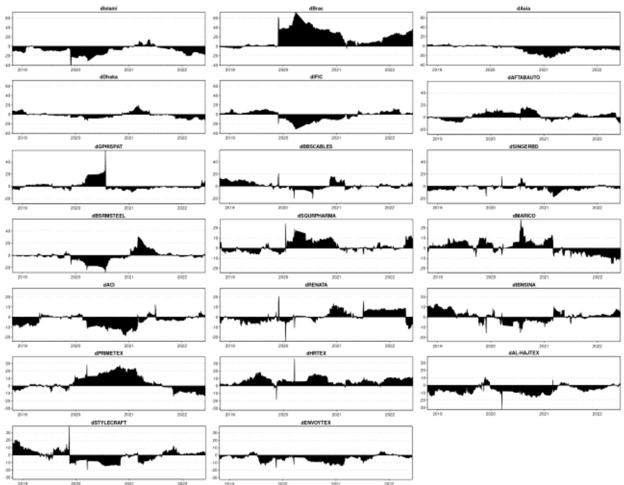

Fig. 7 The net dynamic connectivity of each listed company in the sector under examination using the Diebold and Yilmaz methods. The values on the y-axis are calculated by subtracting the proportion of total spillovers transmitted to other companies from the proportion of total spillovers obtained from other companies. Accordingly, when the net dynamic connectivity is greater than zero, the associated market acts as a net shock transmitter, and vice versa

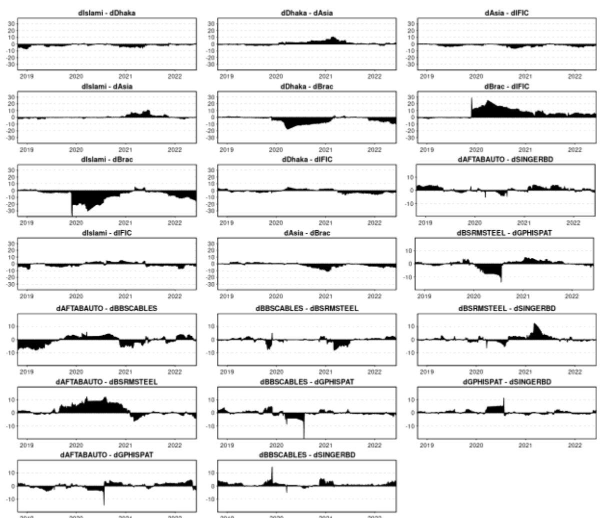

Fig. 8 The net pairwise dynamic connectivity of each of the ten probable pairs of listed companies of Banking and Engineering sectors investigated using the Diebold and Yilmaz methodology. The values on the y-axis are calculated by subtracting the proportion of total spillovers transmitted to other companies from the proportion of total spillovers obtained from other companies

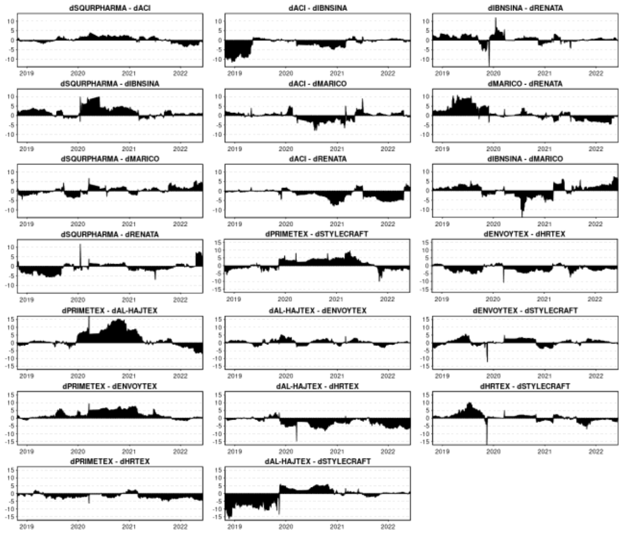

Fig. 9 The net pairwise dynamic connectivity of each of the ten probable pairs of listed companies of Pharmaceuticals and Chemicals, and Textile sectors investigated using the Diebold-Yilmaz methodology. The values on the y-axis are calculated by subtracting the proportion of total spillovers transmitted to other companies from the proportion of total spillovers obtained from other companies

5. Conclusion

Through two alternative methodologies, this study assessed the connectivity of Dhaka stock market sector-wise company returns. The arch and garch parameters are statistically significant and provide a thorough explanation of the volatility. From the discussion of result, due to slower decay, volatility persists for a longer period. It was also observed that the markets were unsteady or unreliable. The DCC-GARCH model can explain both the volatility and the degree of correlation between variables. All the companies had a positive correlation, which is consistent with the sample data correlation results. The main findings are that there is a clear relationship between the sector-wise companies. There is an indication of a consistent time-varying linkage between the companies. That is, the interconnections between the sector-wise companies are convincing and stable over time. The findings of the second approach, Diebold and Yilmaz methodology, are likewise compatible with the findings of the DCC-GARCH model. Dhaka Bank is the most transmitter and receiver of shocks, whereas Islami Bank is the most receiver and Brac Bank is the most transmitter. The most frequently reported shock receivers and transmitters are AFTABAUTO, RENATA, PRIMETEX, and HRTEX.

Similarly, to earlier research, some companies are shock transmitters and receivers, while others are simply transmitters or only receivers of shocks. Individual and net pairwise dynamic connectedness of shock spillover estimated by the Diebold and Yilmaz techniques is identical to DCC-GARCH model approach in that there is evidence of high interconnectivity and spillover effects, which is analogous to past studies in which the two techniques produced nearly identical results. Previous research revealed a clear indication of interconnection and spillover effects, which is comparable to the current study, which shows evidence of interconnectedness and spillover effects.

The Dhaka stock market has seen significant changes in the interconnectedness of stock markets during the last few years. Understanding the flow of returns and the volatility spillovers between sector-wise listed companies and market movement is crucially important for investment strategy and risk management. Therefore, these findings will enhance existing research as well as future developments in Dhaka stock market analyses. Furthermore, the findings will be useful for investors and financial organizations seeking to better understand the linkages between the sector-wise companies in the Dhaka stock market for the purposes of risk management. The outcome of this study is not only useful for a specific country's micro-investors but also for application in other countries. This study only examined one country and had a small sample size; nevertheless, it must expand the number of countries and have a larger sample size, which will be investigated more in the future.

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