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Covid-19 Pandemic and Performance of Economic Sectors in Vietnam

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Abstract: Purpose of the paper: This study aims to consider the Covid impact on stock – price volatility of different industry groups in Vietnam by using the M-GARCH model.

Design/methodology/approach: In order to investigate the impacting level, we observe stock prices of 4 groups consisting of less – affected groups like essential production; heavily - affected industries such as tourism, aviation, petroleum; psychological effects like banking, real estate and beneficial groups like food sectors. Then, we use the dynamic conditional correlation (DCC) model to estimate price volatility as well as correlations among these stock price volatilities before and after the Covid-19 pandemic. Finally, the DCC model also helps to predict the correlation coefficients among these stock price volatilities.

Findings: The empirical result gives some warnings to firms in fighting against Covid-19 pandemic. If the estimated correlation coefficients of stock price volatilities before and after pandemic are unchanged, those economic fields respond consistently to Covid-19. While increasing or decreasing correlation coefficients imply similar - reacted or different – reacted groups. The forecasting results on stock price volatilities from the DCC model also show the economic reaction to the pandemic break out and restoring when the epidemic is basically controlled.

Originality/value: This article investigates the reaction to Covid-19 pandemic from a variety of Vietnamese economic sectors by considering the fluctuations in their stock prices. Moreover, the article also shows the efficiency of the DCC model in estimating the M-GARCH model for correlation coefficients reflecting the reality of the pandemic situation in Vietnam.

Keywords: Covid-19 pandemic, M-GARCH model, Vietnamese economic sectors, stock prices.

1. INTRODUCTION

Coronavirus disease 2019 (Covid-19) has complicatedly taken place all over the world. The heavy Covid impact on the international economy has put all nations in difficult situations and it will take a long time to get back to normal. Most governments have been forced to limit public movements as well as close businesses and venues to slow down the spread of the virus. This makes a devastating impact on the global economy due to increasing inventory costs.

The virus continues its spread across the world, with more than 33 million confirmed cases in 213 countries and deaths passing one million by 25 Sep according to WHO data at the beginning of October 2020. Vietnam has also recorded more than one thousand cases and 35 deaths in 41 provinces. In spite of many efforts, the pandemic seems to keep spreading.

Therefore, businesses have been looking for appropriate solutions to overcome this tough time. However, the fact that the situation never happened in modern times leads to very few experiences and study of this outbreak.

Until now, some research has been made to evaluate the Covid epidemic's influence on business operation. Generally, the disease can affect directly or indirectly to enterprise activities, such as customer demand-variability on medical equipment, Internet services for communication and entertainment.

Recently, many studies have been carried out towards evaluating the effect of other pandemics on corporate performance. (Maphanga, P. M., & Henama, U. S. , 2019) showed that the Ebola virus epidemic has heavily influenced the economies of Western Africa countries, especially in mining, agricultural production and tourism. Low demands in these industries led to the closure of various hotels, airlines, resorts, ...As a result, revenue and profits dropped down while the unemployment rate was rising. Moreover, research from (Overby, J., Rayburn, M., Hammond, K., & Wyld, D. C., 2004); (Lee, G. O., & Warner, M. (2006). , 2006) and (Jung, H., Park, M., Hong, K., & Hyun, E., 2016) on SARS epidemic in China and MERS outbreak in Korea also obtained similar results. In particular, (Jung, H., Park, M., Hong, K.,

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& Hyun, E., 2016) provided evidence of consumers shopping behavior on changing categories of regular shopping goods, reducing purchasing power in order to reduce the risk of infection by movements.

Besides, some authors studied the epidemic impact on specific economic groups' activities. For instance, the effect of SARS epidemic on hotel stock price volatility in Taiwan presented in (Chen, M. H., Jang, S. S., & Kim, W. G. , 2007) displayed a significant SARS impact of on Taiwan hotel market, while (Min, J. C., Lim, C., & Kung, H. H., 2011) pointed out that Japanese domestic tourism hit an extremely low revenue, especially in the first 5 months after SARS outbreak.

If SARS, Ebola or MERS epidemics only occur in certain countries or regions, COVID-19 is a global pandemic. In addition to above influences, there are also some other effects such as: reducing oil prices due to a global declined demand or supply chain failures because of the outbreak. These occurrences easily lead to the capital market reduction, the weaker shopping power and a negative impact on business investments in real estate and finance.

The aim of this study is to investigate COVID-19 effects on enterprise operations of Vietnam industries in short and long terms. Data are stock prices of 4 grouped companies consisting of less – affected groups such as essential production; heavily - affected industries such as tourism, aviation, petroleum; psychological effects like banking, real estate and beneficial groups like food sectors. Using the M-GARCH model, this article analyzes the correlation between industry groups during the COVID pandemic. As a result, it provides evidence of pandemic effects on business performance such as processing industry, essential food, banking, tourism and logistics and so on. Moreover, this result also helps national administration to support businesses to overcome the crisis in this pandemic.

2. LITERATURE AND METHODOLOGY

The most popular and successful volatility models are the autoregressive conditional heteroskedasticity (ARCH) model by (Engle R. F., 1982) and generalized ARCH (GARCH) model by (Bollerslev, 1986). These models work well in time series data, especially for financial time series, such as time–varying volatility and volatility clustering.

In reality, we need to know the relationships between volatilities of multiple markets or asset classes and also variance–covariance of many portfolios, so multivariate volatility models have been developed. There are two common ways to model the multivariate time series, that are used to estimate the variance–covariance matrix directly and the correlation between the variables indirectly.

(Bollerslev, T., Engle, R. F., & Wooldridge, J. M. , 1988) proposed VECH - the first multivariate GARCH model for the conditional variance–covariance matrix. The benefit of this model is that we can directly interpret the model's coefficients. However, the model is general and hard to implement. In the same year, Bollerslev, Engle, and Wooldridge provided a simplified version of the original VECH model called Diagonal–VECH which decreases the number of parameters significantly and facilitates the derivation process of conditions to assure that the variance–covariance matrix is positive definite.

In 1995, (Engle, R. F., & Kroner, K. F., 1995) presented the BEKK model satisfying the requirement that the conditional variance–covariance matrix is positive definite. However, the number of parameters in the BEKK model will be tremendous in case of high data dimensions. Moreover, the BEKK coefficients may fail to interpret as clear as VECH coefficients. The Diagonal–BEKK model was developed as the simplified version of BEKK and has similar advantages and disadvantages like the Diagonal-VECH model.

A different type of multivariate GARCH model is modelling correlation indirectly from time series data. (Bollerslev, T., 1990) proposed a constant conditional correlation (CCC) model in which a conditional correlation matrix is considered to be constant. The assumptions of the CCC model reduce a considerable number of parameters, and ensure the positive definiteness of the variance–covariance matrix. Nevertheless, the specification that the conditional correlation matrix is time–invariant is unrealistic in some cases. Therefore, (Engle R. , 2002) developed the CCC model to create a time-varying conditional correlation matrix. (Engle R. , 2002) introduced the dynamic conditional correlation (DCC) model designated a GARCH–type dynamic matrix process and then transformed the variance–covariance matrix to the correlation matrix. (Tse, Y. K., & Tsui, A. K. C. , 2002) provided the time–varying correlation (TVC) model that treats conditional correlation as the weighted sum of past correlations, with the conditional correlation matrix in the form of ARMA structure.

For modeling financial volatility, GARCH models are popular (Hassan, S. A., & Malik, F. , 2007), (Kang, S. H., Kang, S. M., & Yoon, S. M., 2009); (Sekati, B. N. Y., Tsoku, J. T., & Metsileng, L. D. , 2020); (Kirkulak-Uludag, B., & Lkhamazhapov, Z. , 2017) and (Bohl, M. T., Diesteldorf, J., & Siklos, P. L., 2016) … In addition, multivariate GARCH specifications such as DCC, BEKK, and CCC models are used more frequently than univariate models, which will help analyze the volatility transmission among multiple financial variables.

Consider the DCC multivariate GARCH model (Engle R. , 2002):

$$y_t|F_{t-1} \sim N(0,Q_t), t = 1,2,\dots,n \quad (1)$$

$$Q_t = D_t \Gamma D_t$$

where $y_t = (y_{1t},\dots,y_{mt})', \eta_t = (\eta_{1t},\dots,\eta_{mt})'$ are independently and identically distributed (i.i.d.) random vectors, F_t is the past information available at time $t, D_t = diag(h_1^{1/2}, \dots, h_m^{1/2}), m$ is the number of return, and $t = 1,\dots,n$. As $\Gamma = E(F_{t-1}) = E(\eta_t \eta'_t)$, where $\Gamma = \{\rho_{ij}\}$ for $i,j = 1,\dots,m,$ the constant conditional correlation matrix of the unconditional shock, η_t, is equivalent to the constant conditional covariance matrix of the conditional shocks, ε_t, from Eq. (1), $\varepsilon_t \varepsilon'_t = D_t \eta_t \eta'_t D_t$,

$D_t = (diag\ Q_t)^{1/2}$, and $E(F_{t-1}) = Q_t = D_t \Gamma D_t$, where Q_t is the conditional covariance matrix. The conditional covariance matrix is positive definite if and only if all the conditional variances are positive and Γ is positive definite.

The DCC model assumes that the conditional variance for each return, $h_{it}, i = 1, \ldots, m,$ follows a univariate GARCH process:

$$h_{it} = \omega_i + \sum_{j=1}^{r} \alpha_{ij}\varepsilon_{i,t-1}^2 + \sum_{j=1}^{s} \beta_{ij}h_{i,t-j}$$

where α_{ij} represents the ARCH effect, or short run persistence of shocks to return i, β_{ij} represents the GARCH effect, and $\sum_{j=1}^{r} \alpha_{ij} + \sum_{j=1}^{s} \beta_{ij}$ denotes the long run persistence.

If η_t is a vector of i.i.d. random variables, with zero mean and unit variance, Q_t is the conditional covariance matrix (after standardization, $\eta_t = y_t/\sqrt{h_{it}}$). The η_t is used to estimate the dynamic conditional correlations, as follows:

$$\Gamma_t = \{(diag\ Q_t)^{1/2}\}Q_t\{(diag\ Q_t)^{1/2}\}$$

where the $k \times k$ symmetric positive definite matrix Q_t is given by

$$Q_t = (1 - \theta_1 - \theta_2)Q + \theta_1\eta_{t-1}\eta'_{t-1} + \theta_2 Q_{t-1} \quad (2)$$

in which θ_1 and θ_2 are nonnegative scalar parameters to capture the effects of previous shocks and previous dynamic conditional correlations on the current dynamic conditional correlation, especially $\theta_1 - \theta_2 < 1$. If $\theta_1 = \theta_2 = 0$, Q_t is the same as in the CCC model. As Q_t is conditional on the vector of standardized residuals, (2) is a conditional covariance matrix, and Q is the $k \times k$ unconditional variance matrix of η_t. The DCC model is nonlinear, but could be estimated using a two-step method based on the likelihood function. The method consists of estimating a series of univariate GARCH and then the correlations.

3. EMPIRICAL RESULTS

3.1. Data

To investigate the Covid impact on enterprise operations of Vietnam industries in short and long terms using stock prices, we collect daily data from January 01, 2019 to September 17, 2020 including open prices of Hoa Phat Group (HPG), Vinamilk (VNM), Vietnam Airlines (HVN), Vietcombank (VCB) and NoVaLand Investment Group Corporation (NVL). These firms are selected on the fact that their capital markets are considered to be the largest in the sectors.

Daily data seems to capture the dynamic interaction of oil and stock prices better than weekly and monthly data. The reason is that weekly data cannot deal with holidays and their lead/lag relationships, while monthly data may mask some volatility transmission due to time aggregation and compensation effects. Moreover, daily data reflects fast reaction to level shifts and changes in trends.

In Table 1, volatility is defined as the coefficient of variation over 629 days. Based on the coefficient of variation, we can see that Vietnam Airlines' stock price has the strongest volatility (21.07%), followed by Vietcombank (13.75%) while the prices of Vinamilk and NoVaLand Investment Group Corporation have low volatility of 9.89% and 6.08%, respectively.

The following Figure 1 also shows stock price volatility of firms' shares before and after Covid-19. In Figure 1, we can see that during the second half of the first quarter of 2020, the stock prices all dropped significantly. Since the beginning of the second quarter, when the Covid-19 pandemic in the country was controlled, the stock prices of all sectors tended to increase. However, due to the psychological effect, stocks of real estate sector (represented by NVL) and banking sector (represented by VCB) increase rapidly, especially the material-sector (represented by HPG) is getting up sharply, even higher than the previous period of Covid-19, while the sector of transportation and tourism, represented by Vietnam Airlines, has declined significantly until now.

Table 1. Summary Statistics.

This table reports some numerical statistics of five stock prices. Based on mean and median of stock prices, we can see that Vinamilk' stock price has the highest mean (121278.8 VND), followed by Vietcombank (76400.32VDN) while the prices of Vietnam Airlines have lowest mean (33267.89). Besides, the reasonable differences between mean and median, maximum and minimum values of each variable stock prices that there is no presentation of outliers.

Descriptive Statistics of Stock Prices					
	HPG	**VNM**	**HVN**	**VCB**	**NVL**
Mean	19949.53	121278.8	33267.89	76400.32	58162.94
Median	19625.00	122950.0	34225.00	78700.00	58200.00
Maximum	25400.00	151600.0	45000.00	94500.00	65100.00
Minimum	13500.00	83700.00	17800.00	53500.00	51000.00
Std. Dev.	2253.651	11997.30	7009.381	10505.16	3538.669

Skewness	0.115811	-0.465006	-0.254036	-0.380628	-0.037123
Kurtosis	3.067866	2.993542	1.847898	2.069573	2.063401
Observations	626	626	626	626	626
Coefficent of variation (%)	11.297	9.892	21.070	13.750	6.084

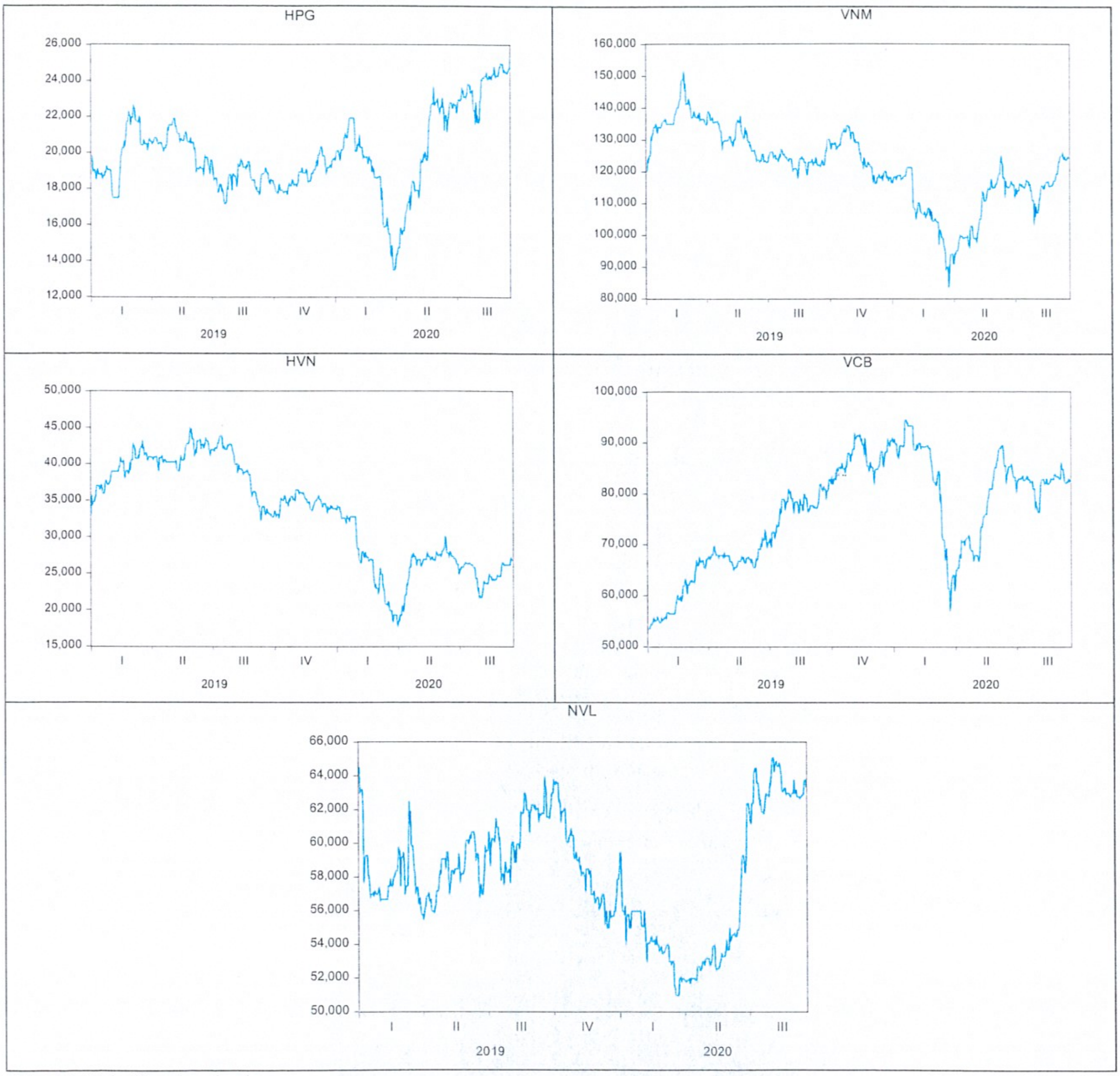

Fig. (1). Volatility of stock prices

In Fig. (**1**), the graph shows that these time series imply all significant volatilities. So, they are non-stationary. Therefore, we proceed to transform this data by taking the first difference of these time series. The result is then illustrated in Fig. (**2**).

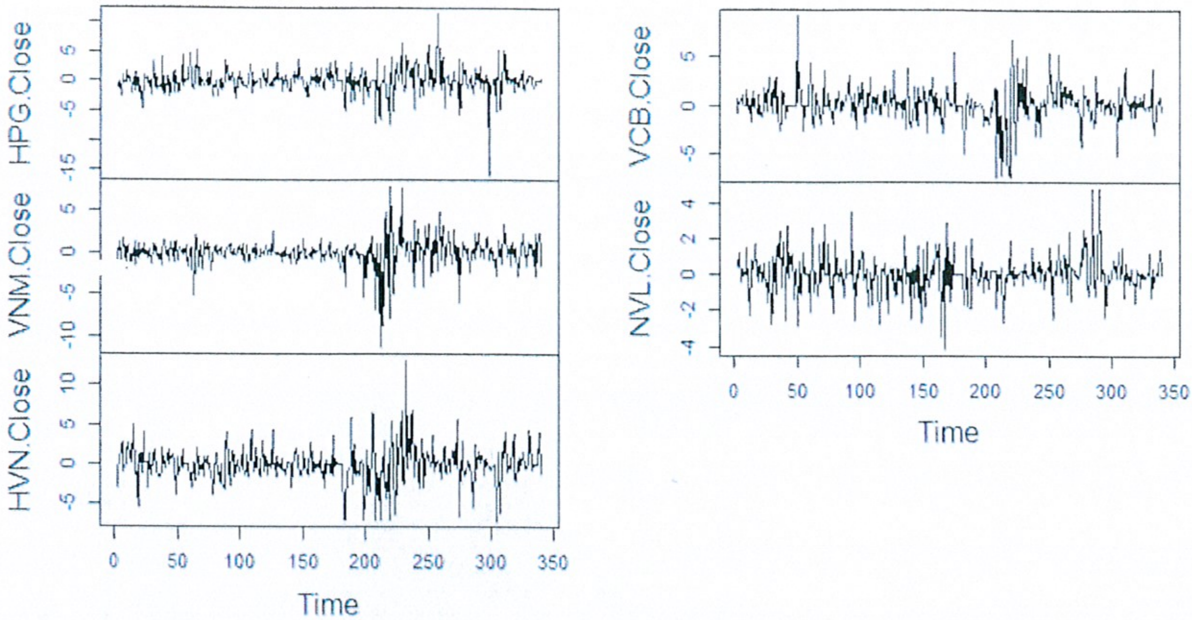

Fig. (2). Graphs of first difference of logarith's time series.

In Fig. (**2**), the stopping time of time series has occurred due to the zero mean of first differences.

3.2. Empirical results

In this research, we will examine the performance of five groups of economic sectors in Vietnam according to pairs of stocks.

In Fig. (**1**), we can see that the time series are non-stationary. Therefore, we proceed to transform this data by taking the first difference of the time series after it has been converted to logarithmic form.

The result is then illustrated in Fig. (**2**). We can see that these time series are all stationary.

Regarding the results of ARCH and GARCH, five models of five companies' stock prices are constructed. The symbol $(\varepsilon_{t-1})^2$ denotes the effects of "news" (unexpected shocks) and h_{t-1} presents the volatility spillover effect.

Generally, in Table 2, stock prices depend on volatility spillover rather than unexpected shocks because range of h_{t-1} values are from 0.73 to 0.96 at a significant level of 1%. At the same level, $(\varepsilon_{t-1})^2$ should range from 0.03 to 0.12. In particular, the stock prices of HPG depend the most on volatility spillover the most due to highest value 0.96 while that of VCB depends the least on volatility spillover because of 0.73. On the other hand, unexpected shocks affect the most in VCB and the least in HPG.

The DCC model estimates the conditional correlations between the volatilities of spot and futures prices based on estimating the univariate GARCH(1,1) model for each stock price. According to (Bollerslev, T., & Wooldridge, J. M. , 1992) on robust t-ratios, the estimates of the DCC parameters, θ_2, are statistically significant in all cases, while θ_1 fail in some cases. This indicates that the assumption of constant conditional correlation for all shocks to returns is not supported empirically.

In table 3, the short run persistence of shocks on the dynamic conditional correlations is statistically significant for the case of VNM & HVN, while the largest long run persistence of shocks to the conditional correlations for HPG & NVL is 0.98.

Figure 3 shows that these correlation coefficients have different changes among the volatility of stock prices in the period before and after Covid-19 such as unchanged, insignificant changed and significant changed. This proves the different effects on a number of stocks representing different sectors of the Vietnamese economy. And the change in the correlation coefficients of these stock price volatilities is matching real situations in Vietnam in particular as well as in the world in general.

Figure 4 uses the last 20 correlation observations to show 10 correlation forecasts. Those results are presented by orange points.

From the results in Figure 4, we can see that correlation coefficients of price volatility tend to recover after big changes due to the serious influences from Covid-19. Specifically, in Vietnam, from the end of July to the beginning of August, the Covid-19 epidemic broke out for the second time and was basically controlled at the end of September, so there existed some stock pairs whose correlations were getting back to normal after decreasing for the first 20 days. This is completely in line with the reality in Vietnam because after a period of social distance to prevent the rapid spread of the

Covid-19 epidemic in the first months of 2020, it seriously affects some areas: such as aviation, real estate, and tourism. Then, by the end of 2020, the fact that the epidemic has basically been controlled in Vietnam made the economy quickly recover which can be seen clearly through the Vietnam stock market.

Table 2. Estimation Results of Bivariate GARCH (1,1) Models.

Stock	Variable	Estimate	Std. Error	t value	Pr(>|t|)
HPG.Close	Mu	-0.03800	0.121659	-0.31237	0.754761
	Ar1	0.773263	0.205044	3.771211	0.000162
	Ma1	-0.75089	0.208783	-3.5965	0.000323
	Omega	0.022274	0.055182	0.403638	0.686479
	Alpha	0.032671	0.009771	3.343856	0.000826
	Beta1	0.966329	0.019268	50.15126	0.000000
VNM.Close	Mu	0.022118	0.055411	0.399161	0.689775
	Ar1	-0.61885	0.128047	-4.83298	0.000001
	Ma1	0.50638	0.112486	4.501713	0.000007
	Omega	0.059892	0.035339	1.694798	0.090114
	Alpha	0.128569	0.052743	2.437637	0.014784
	Beta1	0.859983	0.039295	21.88546	0.000000
HVN.Close	Mu	-0.11752	0.122895	-0.95627	0.338938
	Ar1	-0.13354	0.222172	-0.60105	0.547810
	Ma1	0.318569	0.206049	1.546085	0.122084
	Omega	0.391868	0.347765	1.126816	0.259820
	Alpha	0.104394	0.050716	2.058412	0.039551
	Beta1	0.818472	0.111964	7.310134	0.000000
VCB.Close	Mu	0.128505	0.094564	1.358922	0.174171
	Ar1	-0.48476	0.371000	-1.30663	0.191340
	Ma1	0.570565	0.340724	1.674568	0.094019
	Omega	0.589083	0.474451	1.241609	0.214381
	Alpha	0.083619	0.059866	1.396763	0.162485
	Beta1	0.732336	0.194344	3.768237	0.000164
NVL.Close	Mu	0.008831	0.049244	0.179324	0.857683
	Ar1	0.435478	0.749101	0.581335	0.561015
	Ma1	-0.51077	0.718202	-0.71118	0.476971
	Omega	0.116006	0.119527	0.970541	0.331777
	Alpha	0.084119	0.052126	1.61377	0.106577
	Beta1	0.826167	0.12448	6.63695	0.000000
[Joint]dcca1		0.000000	0.000002	0.000746	0.999405
[Joint]dccb1		0.904945	0.062473	14.48548	0.000000

Information Criteria	
Akaike	18.827
Bayes	19.301
Shibata	18.801
Hannan-Quinn	19.016

Table 3. Result of the DCC Model for Every Pair of Stock Prices.

	HPG& VNM	HPG& HVN	HPG& VCB	HPG& NVL	VNM& HVN	VNM& VCB	VNM& NVL	HVN& VCB	HVN& NVL	VCB& NVL
θ_1	0.0242	0	0.025140	0.002035	0.15665***	0.097204	0	0	0	0.02340
θ_2	0.36562***	0.924850***	0.61282	0.980255***	0.12157	0.055830	0.906909***	0.890674	0.923062***	0.809280***
AIC	7.6986	8.6880	8.0643	7.4834	7.8363	8.2257	6.6108	8.2257	7.4642	6.9905

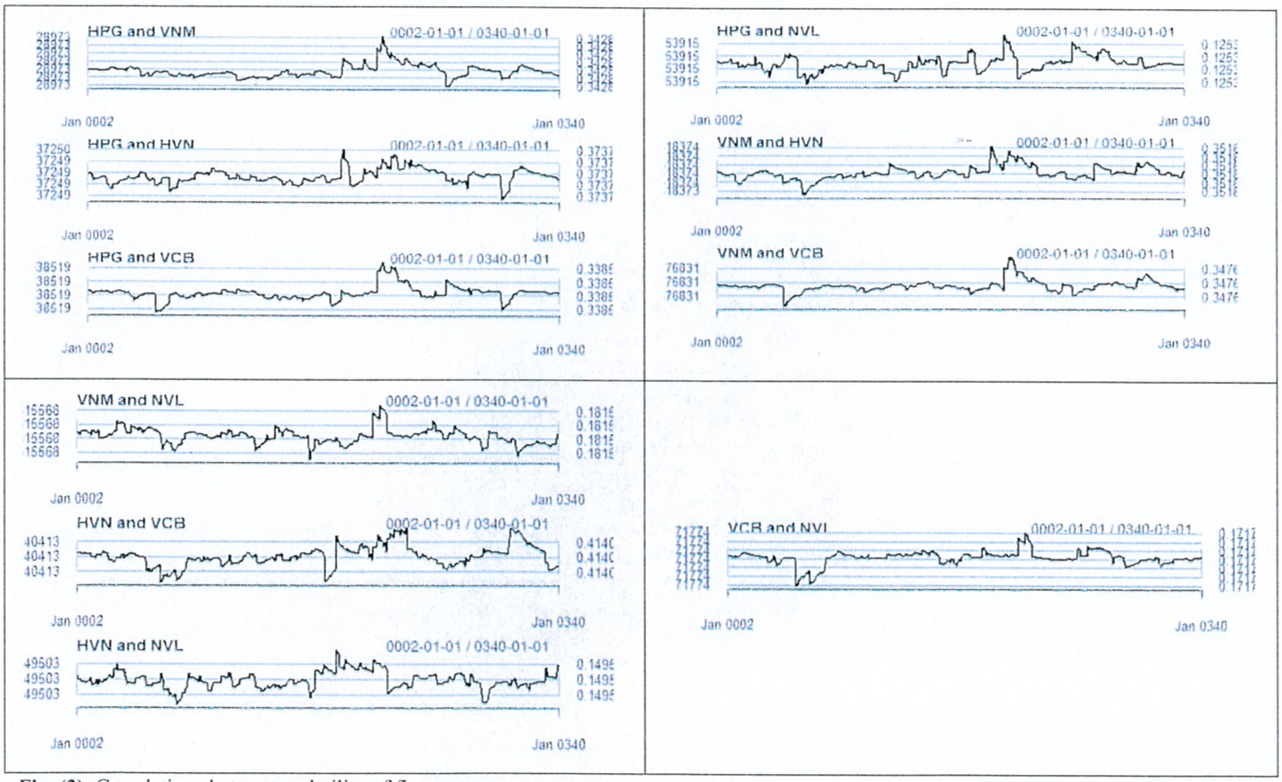

Fig. (3). Correlations between volatility of five assets.

Fig. (**3**) shows correlations between volatility of each stock price pair in 5 selected stocks. Specifically, there was no significant change in the correlation coefficient between some stock pairs, such as a slight increase between HPG and VNM from 0.28973 to 0.3428, VNM and NVL from 0.15568 to 0.1815, HVN and VCB from 0.40413 to 0.4140, on the contrary, the correlation coefficient of price volatility of HPG and VCB decreased slightly from 0.38519 to 0.3385 and this coefficient between HPG and HVN hardly changed (from 0.3725 to 0.3737). This shows that Covid-19 has the same effect on the variation in share prices of these sectors. Meanwhile, this correlation coefficient between VNM and HVN has increased significantly from 0.18374 to 0.3518, showing that these two stocks seem to behave increasingly related under Covid-19. Similarly, the correlation coefficient between the following stock pairs is a quick decline: HPG

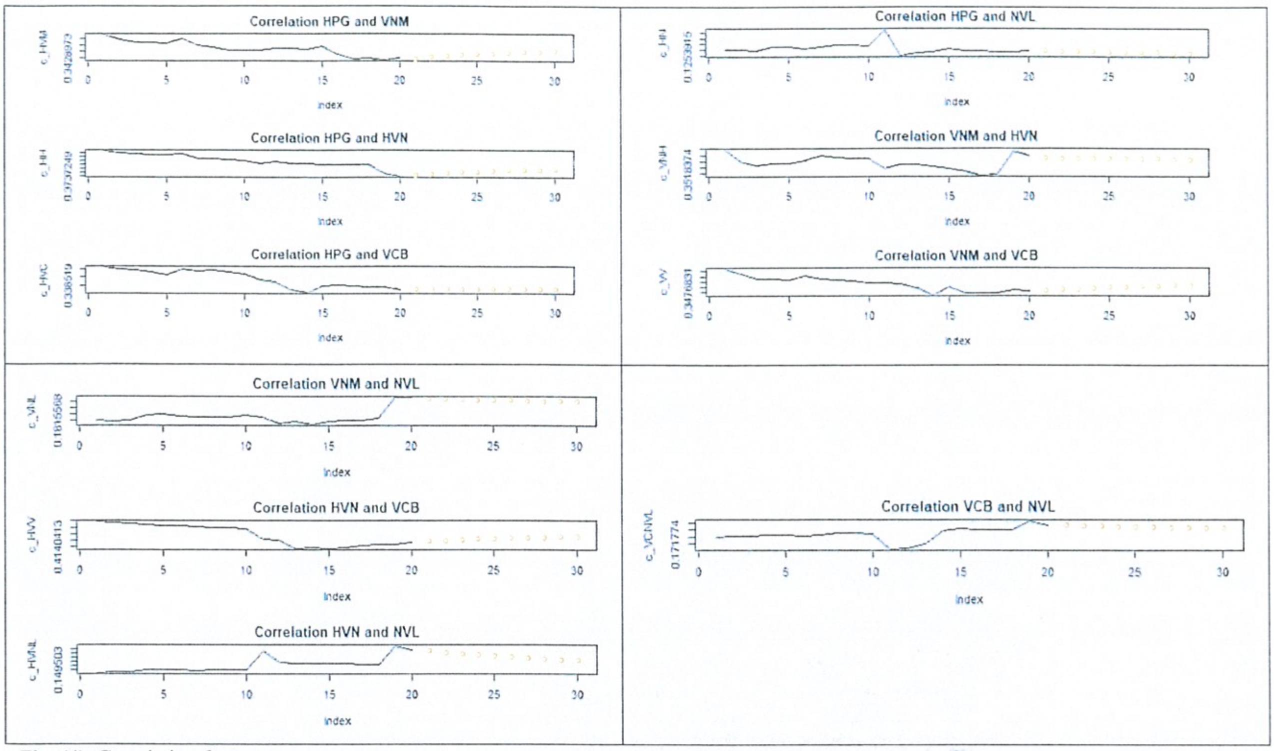

Fig. (4). Correlation forecasts.

and NVL decreased from 0.53915 to 0.1253, VNM and VCB from 0.76831 to 0.3478, HVN and NVL from 0.49530 to 0.1495 and VCB with NVL from 0.71774 down to 0.1717. The significant decline in the correlation coefficient among these stock pairs shows that, with Covid-19, the price volatility of these pairs of stocks tends to be different.

This figure shows the forecasting results of the correlation coefficients of stock price variations. From the results, we see that, after the period when the correlation coefficient decreases or increases due to the influence of Covid-19, they tend to recover. For example, in the period of late August and early September, the correlation coefficient between HPG and VNM decreased, but according to the forecast results, it tends to increase again by the end of September; On the contrary, the correlation coefficient between HVN and NVL increased in early September but tended to decrease at the end of September.

4. CONCLUSION.

This research gives an insight on the performance of five firms' stock prices by using the multivariate GARCH model before and after Covid-19. Our research shows the same trend for all firms with a little bit of a difference in terms of impact. Regarding the individual firms' stock prices, the analysis results show that the HPG and VNM really depend on their first lags while other stock prices show the opposite. Regarding cross-correlation, we can see that HVN and VCB have the highest conditional correlations of 0.414 between the volatilities of spot and future returns.

Using the M-GARCH method, we have confirmed that there are conditional correlations between the volatilities of the time series data. Our result shows that even though the firms' stock prices are affected by Covid-19 news, and the pandemic's severity is different in each economic sector. Therefore, we can see that economic sectors responded differently to Covid-19 pandemic.

We effectively see past volatility and cross-over volatility among the five stocks as most of the coefficients are statistically significant. Furthermore, the results show that the effect of the ARCH effect is stronger than that of the GARCH effect. This means that when the market experiences a shock, stock price volatilities depend more on lags of random error than on past volatilities. Another important conclusion is that cross-effects do not exist across stocks. The stock price of the firms in the study were all influenced by negative news in the past. That is, when there is unfavorable information for the market, the volatility of the markets increases. The results show that HVN's stock price reacts more strongly than other stocks. Thereby, this study implies that it is extremely important to diversify investment portfolios for the purpose of risk management or profit maximization. Investors should not only invest in stocks of companies in one economic sector, they should also consider stocks of companies in other sectors. However, the correlation and risk from stocks of companies in different economic sectors must be weighed and calculated.

Last but not least, a high degree of financial integration can cause negative effects for emerging markets from external shocks, especially those that are unpredictable, such as the recent Covid-19 pandemic. This requires the public authorities where policies are established to regularly assess the full range of factors that exist not only in that country but also in other countries. This will result in making reasonable adjustments to the development strategies.

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CONFLICT OF INTEREST STATEMENT

The authors declare that they have no conflict of interest.

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