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Impact of COVID-19 on the Stock Market Performance of Global IT Sector

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Abstract

Predicting return and volatility in the global Capital Market during a pandemic is challenging, and it is more difficult for a specific sector, particularly if that sector has a positive outlook. The goal of this research is to look at the impact of COVID-19 on the mean and volatility of the Information Technology Indexes of the best nine technology-driven countries based on return performance using an econometric GARCH model that is widely used. The daily returns of information technology indexes are evaluated for the same from November 2018 to February 2021. Data is taken from Yahoo Finance for CAC Tech (France), DAX Tech (Germany), FTSE All Tech (UK), KOPSI 200 IT (Korea), NIFTY IT (India), S&P 500 IT (US), S&P TSX (Canada), SSE_IT (China) and TOPIX17 (Japan). The results show daily positive mean returns for 8 countries' IT Indices and further, an uptrend in mean daily returns is observed in the crisis period for 6 countries' IT Indices. The exogenous variable COVID-19 which was taken as a regressor for the GARCH model was found to be positively significant for IT indices of all the countries. The overall results confirm the presence of the mean-reverting phenomenon for IT indices of all the countries.

Keywords: GARCH, IT, Risk, Return, Volatility

JEL Classification Code: G01, G12, G15, G17

1. Introduction

The COVID-19 pandemic has changed the behaviour of people in various aspects (Michelsen et al., 2020). Be it interacting with others, avoiding social gathering or going to bank/school/colleges/offices/funerals/parties, etc. People have started doing almost all the regular activities remotely, including work from home, online classes, online shopping, online medical services, online banking, digital payments, zoom meetings and many more as technology has enabled them by giving various tools and solutions for continuing the regular activity in a different manner. This pandemic is not only health pandemic but is also economic pandemic which is consistently pushing pressure not only on life but also on livelihood (Bakhshi & Chaudhary, 2020). With so many technological changes in life, the definition of new normal is changing on daily basis. These frequent changes in regular life are raising the questions on involvement of Technology in day-to-day life and the foremost question: Will the technology sector able to leverage the behavioural shifts from COVID-19 and whether the rosy outlook in the sector likely to outlive the pandemic?

Around the world, the IT Indices are outperforming escaping the fallout from COVID-19. The question that demands analysis is whether this rosy outlook is likely to outlive the pandemic? To find the answer to the question, this research takes into consideration the performance of the IT Sector Index of the top 9 countries. They are CAC Tech (France), DAX Tech (Germany), FTSE All Tech (UK), KOPSI 200 IT (Korea), NIFTY IT (India), S&P 500 IT (US), S&P TSX (Canada), SSE_IT (China) and TOPIX17 (Japan). COVID-19 positive cases were increased in 7 countries out of nine countries selected for the study. COVID-19 started in China then moved to the UK, France, and Germany and is in the worst phase in India and America. As these 9 countries are not only pioneers in the use of technology but almost all are impacted by COVID-19, this work emphasizes on impact of COVID-19 on the performance of IT Indexes of these best

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9 technology-driven countries. This paper discusses in more detail the impact of the pandemic on the top 9 countries' information technology industry in the context of the return and volatility.

This paper is divided further into the review of literature, research methodology, analysis, discussion, and conclusion.

2. Literature Review

The contagion COVID-19 Virus has also resulted into a social contagion (Okhuese, 2020) because of the change in behavior in use of technology in every sector be it online health care; blockchain-based monitoring of the pandemic; use of robots to deliver food, medicines and for screening of temperature; online classrooms; working solutions for home; 3D printing technologies ensuring social distance in manufacturing companies; big data analytics; social welfares using AI, etc. (Alam et al., 2020; Strusani & Houngbonon, 2021). Corona can be credited for a vital revolution of the digital infrastructure of industries (George et al., 2020). The health crisis has accelerated the acceptance of technologies along with cloud applications in context of delivery of essential dealings via contactless tools, digital money/ cashless payments etc. From corner to corner i.e. in almost all the industries, use of information technology is in advancement at a speed never seen before even though the effect of pandemic is different on different industries (Hu, 2020). These changes have many consequences on the evolution organization (Iansiti & Lakhani, 2020). In this war with the COVID-19, many technologies including Cloud computing, Artificial Intelligence (AI), Block-Chain technology, 5G Network, etc has the power to bring the change and bring the new normal (Sathish et al., 2020).

When healthcare sector is analyzed in context of Technology use, it can be said that contribution of Technology is massive in terms of detection, diagnosis and controlling the pandemic. Earlier also use of technology was there but there was no or very limited use was there in healthcare in respect to getting the real time data. The IoT is providing a platform so that public-health agencies can monitor the COVID-19 situation. Some of the examples are 'Worldometer' which is a real-time information about COVID-19 worldwide; or a map created by Center for Systems Science and Engineering of Johns Hopkins University taking the data collected from CDC, WHO, China CDC, DXY, etc to give the real time scenario of COVID-19 cases. The use of big data is very helpful in modeling studies of viral activity so that strategies or action plan can be developed by individual countries to face the outbreak (Ting et al., 2020).

In some of them including the educational industry, burst of innovations can be seen along with change in business models from physical to online education. When it comes to education, online classes were there earlier also but no one had imagined to remove classroom from School. This pandemic has enhanced the online classes like anything (Daniel, 2020). The concept of work from home prior to COVID-19 was there in very few industries or in highly advance cities but technology has made work from home as new normal (Goh et al., 2021; Gourinchas, 2020). There are many companies including schools and colleges which had adopted the latest technology for efficient performance of employees during work from home (Bick et al., 2020). Digital payment was also there prior to COVID-19 but with limited use in advance countries but the fear of death has made the digital payment most useful even in emerging and undeveloped countries (Arner, 2020)

Looking at review of various literatures, it can be said that technology disruption is there during COVID but a research is needed to check the performance of IT Sector in terms of return and volatility during COVID period. With increase in volatility, risk increases (Chaudhary et al., 2020). Smaller volatility suggests that share prices are not volatile in shorter run and prices change at a consistent rate over a certain duration (Glosten et al., 1993). The main risk indicator to be considered is volatility and an unfailing forecast of volatility in IT sector is essential (Green & Figlewski, 1999). Higher degree in volatility states the presence of a significant variation in equity price in a shorter run. Standard deviation, skewness and kurtosis are the common measures of risk (Volatility) (Fletcher & Kihanda, 2005; Teplova & Shutova, 2011; Chaudhary et al., 2020). For testing the goodness-of-fit, Jarque–Bera test can be used. Value far-off from 0 shows that the sample is not normaly distributed (Thadewald & Büning, 2007). At the time of financial crunch, the volatility of returns is not measured by normal means but are modelled by using time varying volatility models (Chaudhary et al., 2020; Rastogi, 2014). Engle (1982) proposed the application of the ARCH to integrate the time changing nature of volatility. GARCH models were later developed to eliminate the shortcomings of ARCH by Bollerslev (1986). The GARCH family of models are used to get the most exact outcomes as GARCH is the most standard modelling method for measuring the time series volatility in financial data (Endri et al, 2021; Chaudhary et al., 2020; Hongsakulvasu & Liammukda, 2020).

This study analyzed the performance of Technology/ IT Indexes for the best nine technology-driven countries in the context of mean and volatility in pre COVID-19 and during COVID-19 duration applying the GARCH model. This work is an addition to the present literature in the global investments market. This work also classifies the reaction of the different markets during financial crises and also discovers the reaction in the application of technology during the crisis time and suggests the trend of technology index. This work can be of immense use to portfolio managers for taking calculated decisions for investments in the Technology sector.

3. Research Methodology

3.1. Data Collection

The findings of this work are based on the data taken from Yahoo Finance on the technology indices of the best nine technology-driven countries comprising CAC Tech (France), DAX Tech (Germany), FTSE All Tech (UK), KOPSI 200 IT (Korea), NIFTY IT (India), S&P 500 IT (US), S&P TSX (Canada), SSE_IT (China) and TOPIX17 (Japan). The description of the same is:

Index	Country	No. of IT/Tech Companies
CAC Tech	France	52
DAX Tech	Germany	30
FTSE All Tech	UK	30
KOPSI 200 IT	Korea	11
NIFTY IT	India	10
S&P 500 IT	US	75
S&P TSX IT	Canada	19
SSE_IT	China	47
TOPIX17	Japan	17

Equal windows have been created to consider the pre COVID-19 period from 1 November 2018 to 31 December 2019 as well as during the COVID-19 period from 1 January 2020 to 28 February 2021 to get a better comprehension of technology indices performances.

3.2. Estimation Techniques

Many statistical techniques are used in this study that includes descriptive statistics, the Jarque-Bera test, the unit root test, the ARCH model, and the GARCH (1, 1) test.

3.2.1. Descriptive Statistics

Descriptive Statistics has been done to understand various central tendencies (mean and median) as well as volatility measures (standard deviation, skewness, and kurtosis). The Jarque–Bera test has been used to test the normal distribution. A correlation matrix is applied to find the correlation coefficients between nine IT indices. The mean values of nine IT indices have been computed using the following formula:

$$\mathrm{IR}_{\mathrm{at}} = \ln\left(\frac{P_{\mathrm{at}}}{P_{\mathrm{at}-1}}\right)$$

Where, $\mathrm{IR}_{\mathrm{at}}$ = IT index returns a, P_{at} = closing price of IT index on day t and

$P_{a,t-1}$ = Closing price of the IT index on day t–1

3.2.2. Unit Root Test

The unit-root test was conducted to find the stationarity in a data series. For the said purpose, the Augmented Dickey-Fuller Test was used as follows:

H0 = There exists a unit root

$$\Delta y_t = \propto_0 + \theta y_{t-1} + \sum_{i=1}^{n} \propto \Delta y_t + e_t \qquad (2)$$

where 'y' is time series; 't' indicates time period; 'n' indicates the optimum number of lags; 'α_0' is constant; and 'e' is error term (Brooks, 2002).

3.2.3. The ARCH Effect Test

The ARCH–LM was applied to test the heteroscedasticity using the following Equation

$$u_t^2 = \gamma_0 + \gamma_1 u_{t-1}^2 + \gamma_2 u_{t-2}^2 + \ldots + \gamma_p u_{t-p}^2 + v_t \qquad (3)$$

where 'u' indicates the square of residual calculated by the primary regression model ('p' lags are used for secondary regression models).

The null hypothesis is there is no ARCH effect:

$$\mathrm{H0} = \gamma_0 = \gamma_1 = \gamma_2 = \gamma_{\mathrm{p}} = 0 \qquad (4)$$

3.2.4. GARCH Model

The GARCH (p, q) model can be enumerated as follows:

Conditional Mean Equation

$$y_t = \mu + \lambda_1 y_{t-1} + t \qquad (5)$$

Conditional Variance Equation

$$h_t^2 = \omega + \sum_{i=1}^{q} \alpha_i \varepsilon_{t-i}^2 + \sum_{i=1}^{p} \beta_i h_{t-i}^2 \qquad (6)$$

where y_t indicates conditional mean, h_t indicates conditional variance, ω and μ are constants, λ is the coefficient of lag of y, t is the error term.

The GARCH (1, 1) model mentioned below has p = 1, q = 1, and Equation (6) is converted to Equation (7):

$$h_t^2 = \omega + \alpha_1 \varepsilon_{t-1}^2 + \beta_1 h_{t-1}^2 \qquad (7)$$

where 'α_1' and 'β_1' are coefficients of the ARCH and GARCH. ARCH effect 'α' is the estimation of the answer to shock and GARCH effect 'β' states the time taken for any move to die away. The higher 'α' value shows the more sensitive approach to new info and the higher 'β' value shows a larger amount of time for a shift to die out. The '$\alpha + \beta$' shows the perseverance of the applicable time series and higher values of '$\alpha + \beta$' should incline to 1 and infer larger perseverance in volatility (Rastogi, 2014).

3.2.5. GARCH – The Exogenous Volatility Regressor

To find the effect of COVID-19 on the mean and variance, the model is stretched by using a dummy variable for the COVID-19 period.

Conditional Mean Equation

$$y_t = \mu + \lambda_1 y_{t-1} + \delta_1 \text{ COVID-19}_t + t \tag{8}$$

Conditional Variance Equation

$$h_t^2 = \omega + \alpha_1 \varepsilon_{t-1}^2 + \beta_1 h_{t-1}^2 + \delta_1 \text{COVID-19}_t \tag{9}$$

The dummy variable COVID-19 undertakes a 0 value for the pre COVID-19 period from 1 November 2018 to 31 December 2019 and 1 for the COVID-19 period which is from 1 January 2020 till 28 February 2021. For the conditional mean equation, a negatively significant coefficient for COVID-19 specifies a correlation between COVID-19 and a decrease in the return of the IT Index, whereas a positively significant coefficient for COVID-19 specifies a correlation between COVID-19 and rise in the return of the IT Index. In the conditional variance equation, a negative and significant coefficient for COVID-19 specifies a correlation between COVID-19 and a decrease in the volatility of the IT Index, whereas a positive and significant coefficient for COVID-19 specify a correlation between COVID-19 and rise in the volatility of the IT Index.

4. Results and Discussion

Table 1 summarizes the descriptive statistics for daily means for nine IT indices from the best nine countries. The entire study period, from November 1, 2018, to February 28, 2021, was divided into two parts: the pre-COVID-19 period, from November 1, 2018, to December 31, 2019, as shown in Table 1 Part A, and the COVID-19 period, from January 1, 2020, to February 28, 2021, as shown in Table 1 Part B. As seen in Table 1, the COVID-19 period was separated into two parts: part C and part D.

The mean daily returns of all the country IT Indices show an uptrend during the crisis period (Table 1 Part B) as compared to before crisis period (Table 1 Part A) except for the IT Index of France, UK, and China. The highest and lowest mean daily return during the crisis period was for Germany and UK respectively. Although it is observed that China has the highest mean daily returns and India has the lowest mean daily returns before the crisis period. Further, it is detected that the maximum and minimum values of indices daily mean returns during the COVID-19 period are all obtained in the first seven months of the crisis (Table 1-Part B and Part C). The Standard deviation of daily returns of the first seven months during the crisis period is higher for all indices as compared to the next seven months during the crisis period (Part C and Part D). Comparing the standard deviation of daily returns during the crisis period (14 months) and before the crisis period (14 months) (Table 1 Part A & Part B), the crisis period of fourteen months shows a higher standard deviation of daily returns for all indices. Further on comparing pre COVID-19 period and COVID-19 crisis period, nine IT indices shows higher kurtosis showing a leptokurtic dispersal of returns. Another noteworthy observation is that the next seven months of the COVID-19 period display lesser negative skewness and lesser kurtosis value for the distribution of returns as compared to the previous seven months of the COVID-19 period. The Jarque–Bera test approves return to be abnormal during pre COVID-19 period as well as during the COVID-19 crisis period.

Table 2 covers the high points of periodic return for the fourteen months including during the crisis January 2020 to Feb 2021 and the pre-crisis period from Nov 2018 to December 2019, monitoring for equal length windows. Also, the periodic return of the 1st seven months and the next seven months of the crisis time are shown separately in the Table.

Table 2 reveals that the IT Indices of Korea (69.09%), Germany (66.79%), Canada (58.20%), and India (54.69%) have performed exceptionally well during the fourteen-month crisis period i.e. from 1 January 2020 to 28 Feb 2021. The performance of Composite Indices (Chaudhary et al. 2020) worldwide during crisis period is substandard in comparison to IT Indices periodic returns. Comparing the periodic returns of all indices during the crisis and before the crisis and controlling for equal window lengths, the IT Indices of Korea, Germany and India have shown remarkable growth. The IT Indices of the UK, China, and France have seen a decline in periodic returns during the crisis period when compared to periodic returns of before crisis period controlling for equal window lengths. The IT Indices of Germany and Korea have seen a major uptrend in the next seven months (i.e. 1 August 2020–28 February 2021) of the crisis period.

Table 3 present the correlation between all IT Indices for the period 1 November 2018 to 31 December 2019 and

Table 1: Descriptive Statistics

	CAC TECH	DAX TECH	FTSE ALL TECH	KOSPI 200 IT	NIFTY IT	S&P 500 IT	S&P TSX	SSE_IT	TOPIX17
A. 14 Months Before Crisis Period (1/11/2018 to 31/12/2019)									
Mean	0.000696	0.000633	0.00102	0.00064	0.000157	0.000952	0.00151	0.001605	0.00045
Median	0.001362	–9.34E–05	0.001672	0.000538	0	0.00147	0.002522	0	0.000279
Maximum	0.031678	0.055045	0.039116	0.044012	0.030118	0.066418	0.051584	0.07171	0.027355
Minimum	–0.04639	–0.07699	–0.07188	–0.04786	–0.04795	–0.05201	–0.05021	–0.0862	–0.045857
Std. Dev.	0.012587	0.020194	0.012175	0.012639	0.010184	0.0133	0.013287	0.020339	0.009174
Skewness	–0.27195	–0.30621	–1.00065	–0.13966	–0.47352	–0.27441	–0.52647	0.080886	–0.66474
Kurtosis	3.604815	3.919402	7.363863	4.251425	4.740298	6.374621	4.730284	4.425616	5.740297
Jarque-Bera	8.160155	15.05101	284.2649	20.277	48.41484	144.1677	50.59823	25.38881	114.4132
Probability	0.016906	0.000539	0	0.00004	0	0	0	0.000003	0
Observations	296	296	296	296	296	296	296	296	296
B. 14 Months During Crisis Period (1/1/2020 to 28/02/2021)									
Mean	0.000668	0.001791	–0.0004	0.001738	0.001476	0.001185	0.001591	0.0005	0.000767
Median	0.002212	0.000565	0.000348	0.002904	0.001517	0.003436	0.000454	0	0.000635
Maximum	0.10966	0.125256	0.064508	0.107027	0.086408	0.113002	0.0943	0.058336	0.059832
Minimum	–0.10961	–0.14616	–0.10598	–0.08877	–0.10065	–0.14983	–0.12225	–0.10227	–0.050234
Std. Dev.	0.019975	0.029177	0.017762	0.020831	0.019852	0.024142	0.022009	0.021748	0.012865
Skewness	–0.31892	–0.80988	–1.07486	0.061356	–0.71768	–0.64981	–0.59601	–0.73476	–0.213827
Kurtosis	11.93542	7.824473	9.18489	7.149379	9.309867	11.43904	8.175398	5.616706	6.26488
Jarque-Bera	996.4199	321.581	532.3544	213.969	519.9435	905.2548	350.2203	111.8321	134.6256
Probability	0	0	0	0	0	0	0	0	0
Observations	298	298	298	298	298	298	298	298	298
C. First Seven Months During Crisis Period (1/1/2020 to 31/7/2020)									
Mean	0.000212	0.000114	–0.00052	0.000464	0.000965	0.001255	0.002567	0.002146	–8.29E–05
Median	0.002737	0	0.001143	0.002897	0.001238	0.004214	0.001181	0.001607	0
Maximum	0.10966	0.125256	0.064508	0.107027	0.086408	0.113002	0.0943	0.058336	0.059832
Minimum	–0.109608	–0.14616	–0.10598	–0.08877	–0.10065	–0.14983	–0.12225	–0.10227	–0.050234
Std. Dev.	0.025264	0.036152	0.022071	0.024462	0.024391	0.030625	0.026721	0.02656	0.015385
Skewness	–0.235506	–0.74131	–1.07972	0.168102	–0.7478	–0.54775	–0.75167	–0.91369	–0.116139
Kurtosis	9.185942	6.178023	7.41187	6.871614	7.701673	8.603645	7.2804	4.879802	5.564048
Jarque-Bera	238.9447	76.35013	149.7931	93.76092	151.1268	202.3975	127.7788	42.6699	41.15067
Probability	0	0	0	0	0	0	0	0	0
Observations	149	149	149	149	149	149	149	149	149
D. Next Seven Months During Crisis Period (1/08/2020 to 28/02/2021)									
Mean	0.001125	0.003469	–0.00028	0.003012	0.001988	0.001115	0.000614	–0.00115	0.001616
Median	0.001595	0.0015	0	0.00316	0.001909	0.002242	0	0	0.000981
Maximum	0.034453	0.06495	0.030394	0.050062	0.045728	0.03761	0.041299	0.045727	0.029169
Minimum	–0.033079	–0.0699	–0.0402	–0.04269	–0.04295	–0.06005	–0.03936	–0.04477	–0.031683
Std. Dev.	0.012729	0.019894	0.01208	0.016405	0.013979	0.01522	0.016004	0.015436	0.009695
Skewness	–0.318812	–0.10283	–0.21023	–0.01887	0.065853	–0.79248	0.054356	–0.10561	–0.139845
Kurtosis	2.940511	3.869319	3.57575	3.513463	4.234243	4.82716	3.084904	3.466115	3.553323
Jarque-Bera	2.546055	4.95431	3.15558	1.645637	9.565196	36.32236	0.118126	1.625808	2.386437
Probability	0.279983	0.083982	0.206431	0.439192	0.008374	0	0.942647	0.443568	0.303244
Observations	149	149	149	149	149	149	149	149	149

Table 2: Periodic Returns

Indices	Periodic Return (%)								
	CAC Technology	Nifty IT	S&P 500 IT	DAX Technology	FTSE All Technology	SSE IT	TOPIX17	S&P TSX	KOSPI 200 IT
1 Nov 2018–31 Dec 2019 (14 months before crisis)	22.03	7.05	30.96	16.63	32.63	57.7	19.59	54.48	20.99
1 Jan 2020–28 Feb 2021 (14 months during crisis)	20.11	54.69	39.92	66.79	–12.76	11.86	25.66	58.2	69.09
1 Jan 2020–31 July 2020 (First 7 months during crisis)	1.57	15.04	18.5	–0.54	–9.09	32.69	–1.23	44.36	7.95
1 August 2020–28 Feb 2021 (Next 7 months during the crisis)	18.25	34.47	18.07	67.69	–4.03	–15.7	27.23	9.59	56.64

from 1 January 2020 to 28 February 2021. Table 3 shows a positive correlation across all IT Indices. When comparing Table 3A to 3B, it is observed that the positive correlation in the IT sector across the markets has increased in the crisis period.

The GARCH (1, 1) model for the examination of the time series financial data for the 9 IT indices was examined in this work. The essential criteria of stationarity and the ARCH effect test were used. The ADF test was conducted to examine a unit root. ARCH–LM test was examined to crisscross for heteroscedasticity as well as residuals.

Table 4 shows the outcome of the ADF test along with the ARCH–LM test. As shown in Table 4, all 9 indices in level form possess a greater test-statistic as compared to its critical value; so, the null hypothesis (presence of a unit-root) was rejected and it was concluded that the indices were stationary in the level form at 1% level. The significant values for the probability of LM statistics were found so the null hypothesis (no ARCH effect for seven economies IT Indices) can be rejected confirming the occurrence of the ARCH effect in the residual of the time series model of the means except for Germany and China thus satisfying the criteria to apply the plain vanilla GARCH (1, 1) model for all seven countries except Germany and China.

The findings of GARCH (1, 1) for 7 IT indices are shown in Table 5. The constant in the conditional mean equation for all 7 indices is positive and significant. The lag return variable is negative but significant in a few cases. The coefficient of the constant variance term and the ARCH and GARCH parameters are positive but significant for 7 IT indices in the variance equation, the coefficient in the conditional variance equation, i.e., α-ARCH effect and β-GARCH effect is significant stating that COVID-19 has affected volatility in IT indices. Greater GARCH coefficients indicate that surprises to conditional variance are taking a greater time to die away and volatility is thus ‘persistent’. Table 5 also shows that the sum of the ARCH and the GARCH coefficients ($\alpha + \beta$) is close to unity. If $\alpha + \beta$ is close to one, shock at time t will remain for a larger time. A higher value of $\alpha + \beta$ indicates an ‘extended memory’, and any shock can lead to a constant shift in the future values of β representing that conditional variance is insistent. Furthermore, because the sum $\alpha + \beta$ is less than one, the findings represent a mean-reverting process, confirming that absolute value, $\alpha + \beta$ controls the rate of mean reversion. The S&P 500 IT (US) has the slowest mean reversion, with a volatility half-life of around 29.92 days, while the KOSPI 200 IT (Korea) has the fastest mean reversion, with a volatility half-life of about 5.99 days. The null hypothesis (no change in volatility) is rejected based on the GARCH model results since the change in volatility is considerable.

Table 3: Correlation Matrix

	CAC TECH	DAX TECH	FTSE ALL TECH	KOSPI 200 IT	NIFTY IT	S&P 500 IT	S&P TSX	SSE_IT	TOPIX17
A. Correlation Matrix of IT Indices (Period: 1/11/2018 to 31/12/2019)									
CAC TECH	1.000	0.708	0.619	0.314	0.136	0.588	0.427	0.175	0.238
DAX TECH	0.708	1.000	0.367	0.339	0.017	0.529	0.348	0.268	0.206
FTSE ALL TECH	0.619	0.367	1.000	0.274	0.084	0.345	0.347	0.068	0.200
KOSPI 200 IT	0.314	0.339	0.274	1.000	0.117	0.160	0.114	0.224	0.478
NIFTY IT	0.136	0.017	0.084	0.117	1.000	0.079	0.021	0.029	0.210
S&P 500 IT	0.588	0.529	0.345	0.160	0.079	1.000	0.689	0.090	0.108
S&P TSX	0.427	0.348	0.347	0.114	0.021	0.689	1.000	0.013	0.117
SSE_IT	0.175	0.268	0.068	0.224	0.029	0.090	0.013	1.000	0.152
TOPIX17	0.238	0.206	0.200	0.478	0.210	0.108	0.117	0.152	1.000
B. Correlation Matrix of IT Indices (Period:1/1/2020 to 26/02/2021)									
CAC TECH	1.000	0.782	0.754	0.501	0.578	0.579	0.549	0.162	0.377
DAX TECH	0.782	1.000	0.707	0.448	0.428	0.592	0.525	0.192	0.369
FTSE ALL TECH	0.754	0.707	1.000	0.463	0.502	0.482	0.475	0.172	0.404
KOSPI 200 IT	0.501	0.448	0.463	1.000	0.537	0.253	0.193	0.293	0.554
NIFTY IT	0.578	0.428	0.502	0.537	1.000	0.302	0.284	0.262	0.341
S&P 500 IT	0.579	0.592	0.482	0.253	0.302	1.000	0.774	0.183	0.233
S&P TSX	0.549	0.525	0.475	0.193	0.284	0.774	1.000	0.126	0.259
SSE_IT	0.162	0.192	0.172	0.293	0.262	0.183	0.126	1.000	0.248
TOPIX17	0.377	0.369	0.404	0.554	0.341	0.233	0.259	0.248	1.000

Table 4: Result of ADF and ARCH-LM Test

Particulars	CAC TECH	DAX TECH	FTSE ALL TECH	KOSPI 200 IT	NIFTY IT	S&P 500 IT	S&P TSX	SSE_IT	TOPIX17
ADF in level *T*-statistics	–15.339*	–23.872*	–23.484*	–25.003*	–26.961*	–7.556*	–27.255*	–23.854*	–14.834*
ARCH Effects Obs * *R*-squared	3.601***	0.587	16.151*	161.087*	46.072*	52.561*	9.876*	0.832	46.733*

*Significant at 1% level; ** significant at 5% level; *** significant at 10% level.

The outcome of the GARCH (1, 1) model is shown in Table 6 after adding the COVID-19 variable to the conditional return and variance equations. The result depicts a significant positive impact of COVID-19 on the conditional variance for 7 indices (except the CAC Tech (France) where Z-statistics is not significant but the value is more than one and FTSE All Tech (UK) where the Z-statistics is not significant) showing that COVID-19 has augmented market volatility in all IT indices. Further, it is also found that the COVID-19 variable has a positive significant impact on the mean returns of KOSPI 200 IT (Korea) and Nifty IT (India) only.

Table 5: Results of GARCH (1, 1)

Particulars	**CAC TECH**	**FTSE ALL TECH**	**KOSPI 200 IT**	**NIFTY IT**
	FRANCE	**UK**	**KOREA**	**INDIA**
Conditional Mean Equation				
μ	0.0013	0.0007	0.0016	0.0009
Z-statistics	(2.3992)**	(1.1586)	(2.5655)**	(1.6716)***
λ_1	–0.0742	0.0277	–0.0068	–0.0013
Z-statistics	(–1.5418)	(0.5618)	(–0.1389)	(–.0272)
Conditional Variance Equation				
ω	$1.01 * 10^{-5}$	$9.14 * 10^{-6}$	$2.82 * 10^{-5}$	$1.12 * 10^{-5}$
Z-statistics	(2.3206)**	(2.8541)**	(3.2508)*	(4.1770)*
α (Arch effect)	0.1417	0.0865	0.1588	0.1146
Z-statistics	(4.9050)*	(6.6854)*	(4.5213)*	(5.7890)*
β (Garch Effect)	0.8174	0.8719	0.7319	0.833
Z-statistics	(18.6572)*	(38.4611)*	(12.6787)*	(28.8844)*
$\alpha + \beta$	0.9591	0.9584	0.8907	0.9476
Log likelihood	1690.497	1701.784	1643.184	1721.464
Schwarz criterion	–5.6477	–5.6857	–5.4881	–5.7521

Particulars	**S&P 500 IT**	**S&P TSX**	**TOPIX17**
	US	**CANADA**	**JAPAN**
Conditional Mean Equation			
μ	0.0019	0.0021	0.001
Z-statistics	(3.9929)*	(3.6051)*	(2.5582)**
λ_1	–0.1497	–0.0479	–0.0833
Z-statistics	(–3.3864)*	(–1.1185)	(–1.8933)***
Conditional Variance Equation			
ω	$1.24 * 10^{-5}$	$2.19 * 10^{-5}$	$5.5 * 10^{-6}$
Z-statistics	(3.5214)*	(3.4105)*	(2.6663)**
α (Arch effect)	0.2432	0.1787	0.1229
Z-statistics	(6.1736)*	(4.9036)*	(5.0452)*
β (Garch Effect)	0.7339	0.7446	0.8273
Z-statistics	(18.69)*	(15.7281)*	(23.047)*
$\alpha + \beta$	0.9771	0.9233	0.9502
Log likelihood	1670.701	1635.135	1904.547
Schwarz criterion	–5.5809	–5.461	–6.3696

Note Figures in ( ) indicate the value of *Z*-statistics.

Table 6: GARCH (1, 1) with COVID

Particulars	CAC TECH	FTSE ALL TECH	KOSPI 200 IT	NIFTY IT
	FRANCE	**UK**	**KOREA**	**INDIA**
Conditional Mean Equation				
μ	0.0012	0.0012	0.0006	$7.65 * 10^{-5}$
Z-statistics	(1.8253)***	(1.5457)	(0.8092)	(0.1271)
λ_1	–0.0716	0.0272	–0.0127	–0.0156
Z-statistics	(–1.4779)	(0.5453)	(–0.2518)	(–0.3383)
δ (COVID)	0.0002	–0.0012	0.0021	0.0022
Z-statistics	(0.2118)	(–0.9932)	(1.6945)***	(1.9312)**
Conditional Variance Equation				
ω	$8.49 * 10^{-6}$	$8.56 * 10^{-6}$	$2.73 * 10^{-5}$	$8.95 * 10^{-6}$
Z-statistics	(2.2165)**	(2.6474)**	(2.9936)*	(2.9202)**
α (Arch effect)	0.1393	0.0839	0.145	0.0829
Z-statistics	(4.6235)*	(5.8133)*	(3.9101)*	(4.5042)*
β (Garch Effect)	0.8141	0.8722	0.7161	0.8488
Z-statistics	(17.8980)*	(35.9803)*	(10.4532)*	(23.4697)*
δ (COVID)	$5.9 * 10^{-6}$	$1.97 * 10^{-6}$	$1.47 * 10^{-5}$	$9.27 * 10^{-6}$
Z-statistics	(1.6199)	(0.8852)	(1.8873)***	(3.3004)*
$\alpha + \beta$	0.9534	0.9561	0.8611	0.9317
Log likelihood	1692.004	1702.713	1647.002	1727.923
Schwarz criterion	–5.6312	–5.6673	–5.4794	–5.7524

Particulars	S&P 500 IT	S&P TSX	TOPIX17
	US	**CANADA**	**JAPAN**
Conditional Mean Equation			
μ	0.0023	0.0019	0.0009
Z-statistics	(3.8502)*	(2.6404)**	(1.9457)**
λ_1	–0.1384	–0.0501	–0.0812
Z-statistics	(–3.0359)*	(–1.1513)	(–1.8792)***
δ (COVID)	–0.0006	0.0005	0.0004
Z-statistics	(–0.6022)	(0.3832)	(0.4919)
Conditional Variance Equation			
ω	$7.40 * 10^{-6}$	$1.93 * 10^{-5}$	$4.70 * 10^{-6}$
Z-statistics	(2.7921)**	(3.361)*	(2.6285)**
α (Arch effect)	0.2275	0.1692	0.1252
Z-statistics	(5.7611)*	(4.4871)*	(4.3877)*
β (Garch Effect)	0.7357	0.741	0.804
Z-statistics	(19.3872)*	(14.5267)*	(18.8323)*
δ (COVID)	$1.61 * 10^{-5}$	$1.17 * 10^{-5}$	$6.34 * 10^{-6}$
Z-statistics	(2.9436)*	(1.7960)***	(2.7351)**
$\alpha + \beta$	0.9632	0.9102	0.9292
Log likelihood	1677.38	1637.098	1910.407
Schwarz criterion	–5.5819	–5.446	–6.3678

Note Figures in ( ) indicate the value of *Z*-statistics.

5. Conclusion

This research looks at the impact of COVID-19 on the performance of the leading nine technology-driven countries' IT indices. Data was collected daily from November 2018 to February 2021. In the COVID-19 period, i.e. January 2020 to February 2021, the descriptive statistics reveal a daily positive and higher mean return. Furthermore, for almost all IT Indices, the period demonstrated increased standard deviation, negative skewness, and kurtosis of daily returns. In comparison to the first seven months of the crisis, the data shows that the next seven months of the crisis have decreased standard deviation, negative skewness, and kurtosis of daily returns for all IT Indices. During the COVID-19 period, the daily returns data show mostly negative skewness and increased kurtosis. Furthermore, the correlation matrix shows an increase in the degree of cohesiveness between nine IT metrics over the course of COVID-19.

The COVID-19 coefficients in the conditional variance equation have a large positive influence on conditional variance for all 9 IT Indices, showing that the COVID-19 has exacerbated the volatility in IT Indices, according to the GARCH results. The research also found that all seven indexes went through a mean-reverting process, suggesting that the total of the alpha and beta coefficients is less than 1, indicating that the IT Sectoral returns of all seven markets will return to their prior average values after a period of time. The mean reversion incidence provides an opportunity for investors to estimate the price of a company in the future while taking previous values into account. Further, the COVID-19 coefficient in the conditional mean equation indicates a positive significant effect on the mean return of two IT Sectoral Indices.

Given the intrinsic ambiguity in the present situation, it is tough to forecast the economic impact of COVID-19 in the longer run as COVID-19 is still spreading. In fact, the pandemic has created huge tailwinds for the IT Sector by inciting behavioral shifts that will long outlive the health crisis This study shows that all countries Information Technology sector indices are mean-reverting ones. Even as blockbuster earnings continue, economic recovery and regulatory challenges may cause IT indexes to return to mean values. Still, the impact of COVID-19 cannot be determined because the virus is still spreading. Perhaps the positive outlook in this industry will outlast the pandemic, as it takes advantage of the COVID-19 behavioral shift to expand and invest in emerging technology. The fact that mean returns have been considerably influenced in India and Korea indicates that there will be disruption, and when disruption occurs, mean reversion will be the most dangerous delusion we can have. It is also recommended that investors keep track of IT stocks and consider holding them if volatility continues to decline without a decrease in mean returns since this will indicate a disruption.

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