Impacts of COVID-19 on Stock Markets: Evidence from Stylized Facts of Technology Companies

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Abstract—The outbreak of the COVID-19 pandemic in 2019 has significantly impacted the stock market. The aim of the present study is to investigate whether the COVID-19 pandemic changed the statistical properties of stock return series and whether some stylized facts, which referred to the consistent characteristics across various instruments, markets, and periods, still holds true based on stock data of 34 US technology companies. Some of the common statistical properties of stock returns data include the absence of autocorrelations, volatility clustering, negative skewness and existence of cross-correlations of absolute returns, amongst others. The analysis in this study is based on the stock data of 34 US companies that have large market capitalizations. The pre-Covid data shows an absence of autocorrelation. Contrastingly, this study shows that autocorrelation exists under the circumstances of COVID-19. This study also demonstrates that volatility clustering exists both before and during the pandemic. Moreover, the stock market during the pandemic is more volatile than before. The study also contradicts the stylized fact of negative skewness of return series and about 50% of the companies' return series also show positive skewness. Furthermore, the data disputes the existence of cross-correlations between absolute returns across multivariate series.

Keywords—Stylized facts; COVID-19; US stock market

1 INTRODUCTION

1.1Background

A stylized fact is a simplified portrayal of an empirical result that is typically used in the social sciences, particularly economics [7]. It is often a broad summary of facts that, although generally accurate, may have inaccuracies in the details. Although different stocks may be influenced by different financial statuses and events, the results from empirical studies indicate that financial series do share many statistical properties. Such properties include characteristics such as the absence of autocorrelation, volatility clustering, negative skewness and existence of cross-correlations of absolute returns. The existence of these stylized facts may offer readers and investors new insights that can be used to inform their investment decisions.

Although the statistical properties of stock series have been well researched, we cannot ignore the impact of COVID-19 on the stock market. Notably, the COVID-19 pandemic has had a profound impact on both the global economy and stock markets. In March 2020, the US stock market engaged four circuit breakers in 10 days, out of a total of five used in the history of the US stock market. On March 15, 2020, in response to the economic stagnation caused by the

MSIEID 2022, December 09-11, Chongqing, People's Republic of China

DOI 10.4108/eai.9-12-2022.2327736

COVID-19 pandemic, the Federal Reserve announced a quantitative easing program worth more than $700 billion. Quantitative easing (QE) is an unconventional form of central bank monetary policy wherein the central bank buys long-term debt securities in order to increase the money supply, thus encouraging lending and investment. Meanwhile, these securities can also be purchased on the open market, which adds new funds to the economy, and through the bidding to buy fixed-income securities, lowers interest rates.

Considering the far-reaching impact COVID-19 has had on the stock market and the continuing spread of the virus, we humans will have to adjust to this new normal and learn to live with the virus for the foreseeable future. Therefore, the stock market will also continue to be affected by the pandemic and attempts to control it. On this basis, how the stock market behaves in the COVID-19 context is a topic warranting further research. The aim of this paper is to investigate whether the COVID-19 pandemic changed the statistical properties of stock return series and whether some stylized facts remained unchanged despite the influence of the pandemic. COVID-19 may invalidate some of the presumed facts and it is worth investors knowing more about this situation, as the invalidation of some of the stylized facts may invalidate or validate the use of many predictive models and change investors' investment decisions. Our goal is to "let the data speak for itself" and there is no statistical model used in this paper.

1.2 Related Research

1) Financial Stylized Facts: Cont [6] provided a collection of stylized empirical facts derived from the statistical study of price fluctuations in a variety of financial markets. He discussed some of the broad difficulties that apply to all statistical analyses of financial time series and various statistical aspects of asset returns: distributional properties, tail properties and severe fluctuations, pathwise regularity, and linear and nonlinear dependency of returns over time and across stocks. He went on to demonstrate how these statistical qualities invalidate a large number of the statistical methodologies commonly used to study financial data sets and discussed some of the statistical issues that arise in each situation.

Shakeel and Srivastava [15] investigated the features and stylized facts presented by the S&P CNX Nifty futures index's high-frequency financial time series data. They found that the majority of stylized facts were connected to observable empirical behaviors, distributional features, autocorrelation functions, and the seasonality of high-frequency data. Knowledge of such data may aid in the development of more robust empirical models for analysis.

2) COVID-19's impact on the finance industry: Al-Awadhi et al. [1] investigated if communicable infectious illnesses have an effect on stock market performance. They employed panel data analysis to examine the influence of the COVID19 virus on the Chinese stock market. The data revealed that daily increases in the number of confirmed illnesses and deaths caused by COVID-19 had a substantial negative influence on stock returns across all of the firms in the dataset.

Topcu and Gulal [16] determined the effect of COVID-19 on developing stock markets from March 10 to April 30, 2020, by utilizing panel data analysis. Their study's findings indicate that the pandemic's negative influence on developing stock markets steadily diminished and began to taper off by midApril. They also concluded that the pandemic had the greatest effect on Asian developing markets, whilst emerging markets in Europe were least impacted.

Additionally, they observed that the time governments took to react and the size of the stimulus supplied were critical in mitigating the pandemic's consequences.

He et al. [11] conducted an empirical assessment of the market performance and reaction patterns of Chinese businesses to the COVID-19 pandemic by deploying an event study technique. Through their analysis, they concluded that the pandemic had a negative impact on the transportation, mining, electrical and heating, and environmental sectors. Contrastingly, the manufacturing, information technology, education, and health care sectors remained robust despite the epidemic.

2 METHOD AND DATA

The main purpose of this paper is to investigate the statistical properties of stock return data based on stylized facts derived from large market capitalization US technology companies. On this basis, 34 US technology companies were selected: Apple, Microsoft, Amazon, GooG, GOOGL, Facebook, Salesforce, Oracle, Nvidia, Taiwan semiconductor manufacturing, Paypal, Asml, Adobe, Cisco Systems, Verizon Communications, Intel, Broadcom, ATT, Texas Instruments, Shopify, Sap, T-mobile, Intuit, Qualcomm, Advanced Micro Devices, International Business Machine, ServicdeNow, Snap, Applied Materials, Square, Infosys, Dell technologies, Lam Research Corporation, and Workday. The daily stock data for all of these companies were retrieved from Yahoo Finance. The time span of the stock data ranges from December 2018 to December 2020. To make a fair comparison of how statistical properties changed between before the onset and during the pandemic, the stock data were split into two parts, the first is from December 2018 to December 2019, whilst the second is from December 2019 to December 2020.

The main focus of this research is to visualize the statistical properties of the stock returns. Python is used to handle the return data and produce plots. In this paper, normalized returns are used, which can be calculated using the equation shown below:

$$x_i = \frac{\log \frac{s_i}{s_{i-1}}}{\sqrt{t_i - t_{i-1}}} \tag{1}$$

Where s_i represents asset price at time *i* and t_i represents the day number at time *i*.

3 RESULTS

3.1 Absence of linear autocorrelation

It is widely accepted that price changes in liquid markets display little autocorrelation. In the field of quantitative investments, the goal of the research carried out is to model the time series of investment products' return rates by statistical means to infer whether there are any characteristics between the return rate of different trading days in the series. This information can be used to produce the future return rate and generate trading signals. Of the many characteristics a time series may exhibit have, autocorrelation is one of the most important ones, since using autocorrelation to build models can greatly improve the accuracy of trading signals. An example of this is the mean-reversion strategy of paired trading, which uses the negative correlation between a pair of portfolio spreads to generate a long or short trading signal and generate profit.

In order to investigate the presence of autocorrelation in the stock return series, the Ljung-Box test is employed. The Ljung–Box test is a form of statistical test that determines if any of a time series' autocorrelations are greater than zero. Rather than examining the randomness at each separate lag, it examines "overall" randomness across a range of lags [4]. The definition of null hypothesis and alternative hypothesis of Ljung–Box test are as follows:

- H_0: The data are independently distributed.
- H_α: The data are not independently distributed; they exhibit serial correlation.

The test statistic is:

$$Q = n(n+2)\sum_{k=1}^{h}\frac{\widehat{\rho}_k^2}{n-k} \tag{2}$$

Where n is the sample size, h is the number of lags being tested and $\widehat{\rho}_k^2$ is the sample autocorrelation squared at lag k. Under H_0, the statistic Q asymptotically follows $\chi^2_{1-\alpha,h}$. For significance level α, the critical region for rejecting the randomness hypothesis is as follows:

$$Q > \chi^2_{1-\alpha,h} \tag{3}$$

Where $\chi^2_{1-\alpha,h}$ is the quantile of the χ^2 distribution with h degrees of freedom. Table 1 below shows the statistics of the Ljung–Box test. As shown in Table 1, prior to COVID-19, most of the p-values are greater than 0.05, meaning that the null hypothesis is not rejected. Therefore, the stock returns data do not exhibit autocorrelation before the pandemic. However, for the stock data during the COVID-19 pandemic, most of the p-values are less than 0.05, which reveals that the null hypothesis for most of the cases should be rejected. From this, it can be concluded that the stock returns data indeed shows autocorrelation during the COVID-19 pandemic.

Table 1 The Statistics of The Adopted Data Before and During the Covid-19 Pandemic

	Pre-Covid		**During-Covid**	
Company	**Ib_*stat***	**Ib_p*value***	**Ib_*stat***	**Ib_p*value***
AAPL	26.10	0.16	196.728	2.75e−08
MSFT	18.65	0.55	237.15	3.74e−13
GOOG	30.14	0.07	211.13	6.13e−10
GOOGL	28.88	0.07	211.64	5.33e−10
CRM	20.40	0.43	139.69	5.40e−03
ORCL	16.92	0.66	207.88	1.47e−09
FB	18.28	0.57	178.29	2.45e−03
NVDA	22.39	0.32	215.47	1.86e−10
TSM	19.44	0.49	161.68	9.28e−05
PYPL	16.20	0.70	149.72	9.52e−04
ASML	29.81	0.07	201.19	8.64e−09

ADBE	14.98	0.78	240.46	1.40e−13
CSCO	20.93	0.40	192.64	7.70e−08
VZ	15.88	0.72	182.61	8.92e−07
INTC	28.47	0.10	206.10	2.37e−09
AVGO	11.92	0.92	215.20	2.01e−10
T	18.46	0.56	170.13	1.54e−05
TXN	21.09	0.39	327.98	4.73e−26
SHOP	22.01	0.34	101.51	4.39e−01
SAP	16.79	0.67	140.31	4.88e−03
TMUS	18.94	0.53	133.23	1.48e−02
INTU	14.48	0.81	177.12	3.22e−06
QCOM	26.75	0.14	194.83	4.43e−08
AMD	23.69	0.26	150.60	8.09e−04
IBM	19.97	0.46	149.49	9.93e−04
NOW	17.05	0.65	153.04	5.13e−04
SNAP	12.32	0.90	69.92	9.90e−01
AMAT	21.79	0.35	227.07	7.08e−12
SQ	18.62	0.55	98.88	5.13e−01
INFY	14.89	0.78	133.89	1.34e−02
DELL	15.42	0.75	150.61	8.08e−04
LRCX	26.48	0.15	214.60	2.37e−10
WDAY	14.64	0.80	141.92	3.74e−03
AMZN	16.51	0.68	130.58	2.17e−02

Autocorrelation reflects a certain inherent characteristic of the time series (such as trend or mean reversion), and this inherent characteristic can be continued (at least for a short period of time in the future). The existence of autocorrelation of the stock return rate of data whilst COVID-19 was ongoing indicates that investors could find a suitable time series autoregressive model by fitting historical data. Based on the assumption that history will be repeated in the future, this autocorrelation is statistically expected to exist in future sequences. Since this model accounts for this autocorrelation, it will help investors to predict future movements in the market. However, for the data prior to COVID-19, there is neither autocorrelation nor partial correlation, which indicates that it is a random walk process. Such a process cannot build any model by itself because it cannot make predictions based on the past.

3.2 Extreme returns appear in clusters (volatility clustering)

Volatility clustering, which is also one of the most significant stylized facts in financial markets, refers to the observation that large price fluctuations are often followed by large price changes. By way of contrast, small price changes are typically followed by small price changes. In other words, asset price swings exhibit a cyclical pattern of high and low volatility events. Since Mandelbrot [14] first observed volatility clustering in commodity prices, it has been frequently found and recorded in stocks, market indexes, and currency rates. Despite the considerable development that has been achieved in relation to various statistical models based on Engle's [9] and Bollerslev's [3] ARCH and GARCH models, these models can only offer a very limited economic explanation for the process of creating volatility clustering.

The standard deviation measures how widely prices are scattered compared to the average price. The standard deviation will be minimal if prices move in a small range. Conversely, large standard deviation indicates considerable volatility. Larger returns are usually associated with increased volatility, whereas smaller returns are associated with less potential risks. Volatility often demonstrates strong positive autocorrelation and persistence. This is a quantitative manifestation of the well-known phenomena of volatility clustering, which as stated above, posits that huge price fluctuations are more likely to be followed by subsequent significant price fluctuations.

In the present study, moving standard deviation is used to measure the volatility of the market. Whilst a moving standard deviation makes no forecasts about the direction of the market, it may act as a confirming indicator. The size of each window is defined as 5 here and the standard deviation of every 5 rows are calculated. The moving standard deviation is calculated by computing the return series' 5-period Simple Moving Average. The sum is then calculated of the squares of the difference between the return series and the Moving Average over each of the preceding 5 time periods. Finally, the result is divided by 5 and square rooted. Meanwhile, a K-means clustering algorithm is built in python to calculate the moving standard deviations of return series of stock data before and during COVID-19. K-means clustering is a method for unsupervised machine learning that divides a data set into K clusters. In other words, given a collection of data, K-means clustering attempts to categorize it–typically without previous knowledge of where to begin or without input on whether the final grouping is correct. To group the volatility as low volatility, middle volatility and high volatility, 3-means clustering is utilized and conducted via several major steps. The first step is to initialize 3 centroids, one for each cluster. After that, each point in the data set is assigned to its nearest centroid and the centroid of each cluster is then recalculated. The preceding steps are then repeated until the centroid no longer changes or until a certain number of iterations is reached. Table 2 below shows the clustering final results.

Table 2 Proportion of Each Volatility Group

	Pre-Covid			**During-Covid**		
Company	**Low Volatility**	**Middle Volatility**	**High Volatility**	**Low Volatility**	**Middle Volatility**	**High Volatility**
AAPL	0.86	0.14	0.00	0.50	0.42	0.08
MSFT	0.94	0.06	0.00	0.62	0.32	0.06
GOOG	0.88	0.12	0.00	0.66	0.26	0.08
GOOGL	0.86	0.14	0.00	0.64	0.28	0.08
CRM	0.82	0.18	0.00	0.44	0.44	0.12
ORCL	0.88	0.12	0.00	0.74	0.22	0.04
FB	0.90	0.10	0.00	0.58	0.34	0.08
NVDA	0.80	0.20	0.00	0.70	0.22	0.08
TSM	0.90	0.10	0.00	0.40	0.52	0.08
PYPL	0.92	0.08	0.00	0.64	0.30	0.06
ASML	1.00	0.00	0.00	0.88	0.08	0.04
ADBE	0.88	0.12	0.00	0.62	0.34	0.04
CSCO	0.80	0.20	0.00	0.56	0.36	0.08
VZ	0.68	0.32	0.00	0.54	0.36	0.10

INTC	0.92	0.08	0.00	0.72	0.24	0.04
AVGO	0.86	0.14	0.00	0.70	0.26	0.04
T	0.70	0.30	0.00	0.50	0.42	0.08
TXN	0.70	0.30	0.00	0.58	0.34	0.08
SHOP	0.56	0.42	0.02	0.40	0.46	0.14
SAP	0.66	0.30	0.04	0.54	0.34	0.12
TMUS	0.96	0.04	0.00	0.48	0.46	0.06
INTU	0.98	0.02	0.00	0.76	0.18	0.06
QCOM	0.92	0.04	0.04	0.64	0.32	0.04
AMD	0.54	0.30	0.16	0.42	0.42	0.16
IBM	0.88	0.12	0.00	0.64	0.28	0.08
NOW	0.80	0.20	0.00	0.58	0.34	0.08
SNAP	0.74	0.26	0.00	0.68	0.20	0.12
AMAT	0.82	0.18	0.00	0.60	0.36	0.04
SQ	0.86	0.14	0.00	0.62	0.32	0.06
INFY	0.92	0.08	0.00	0.56	0.38	0.06
DELL	0.80	0.20	0.00	0.68	0.24	0.08
LRCX	0.92	0.08	0.00	0.74	0.20	0.06
WDAY	0.92	0.08	0.00	0.70	0.22	0.08
AMZN	0.80	0.18	0.02	0.32	0.54	0.14

Table 2 shows that technology companies’ stocks became more volatile during COVID-19 than they were before, since more of their volatilities are classified as high volatility. This finding is in line with expectations, given that the economic shutdown caused by COVID-19 severely hit the stock market and ended the longest bull market in the history of the United States. Nevertheless, the vision for economic recovery subsequently pushed the stock market to rebound rapidly, and the United States emerged from the shortest bear market in history. Therefore, we should expect the stock market to exhibit higher volatility and be less stable than before. However, the proportion of high volatility is still relatively small, and the low volatility group still remains the dominant group, which means that even in the COVID-19 context, large capatalization technology stocks can still serve to reassure cautious investors, especially in tough times. These stocks remain very stable during the pandemic, so investors can minimize the risk they are exposed to. This can protect investors from sharp investment setbacks and also allow them to participate in sharing upside opportunities.

3.3 The stock market exhibits occasional large drops but not equally large increases: the returns distribution is negatively skewed

In statistics, a negatively skewed (sometimes called left-skewed) distribution is a form of distribution in which more values are concentrated on the right side of the distribution graph whilst the left tail is longer. In finance, the idea of skewness is used to analyze the distribution of investment returns. Although many finance theories and models assume that security returns adhere to a normal distribution, in reality, returns are often skewed. The distribution’s negative skewness suggests that an investor might anticipate numerous modest wins and a few huge losses. Indeed, it is because of this that many traders’ trading methods are based on negatively skewed distributions. While techniques based on negative skewness may provide consistent returns, an investor or trader should be mindful of the possibility of big losses. Thus, it is critical to appropriately analyze the risks associated with trading methods and to factor in the skewness of the returns.

Many researchers tend to assume the return series follows a normal distribution since the statistical analysis of stock returns can be simplified, allowing the analyst to focus on the first two moments. However, higher moments also contain valuable information and are useful for model building. The higher-order moments are important in modeling stock return series since higher-order moments have distinct economic implications when viewed through the lens of empirical finance studies. Johnson and Schill [5] propose that the Fama-French factors (SMB and HML) may be considered as proxy measures of higher-order co-skewness and co-kurtosis. The researchers demonstrated that when higher-order systematic co-moments are included in cross-sectional regressions of portfolio returns, Fama-French loadings are rendered unimportant.

What's more, in the "new" portfolio theory put forward by Jurczenko and Maillet [12] higher-order moments and the works linked therein are treated as extra risk instruments. Additionally, according to the underlying theory of stochastic dominance, portfolio selection is controlled not only by the conditional mean and variance, but also by the skewness and kurtosis. Harvey et al. [10] and Cvitanic et al. [8] offer evidence to support the validity of the new portfolio theory. Additionally, Andersen and Sornette [2] and Malevergne and Sornette [13] demonstrate that by factoring higher-order moments risk into portfolios, the anticipated return can feasibly be boosted whilst decreasing risk. Thus, change in skewness is an important factor that many researchers should consider before building any predictive models.

In this paper, skewnesses of the return series before and during Covid are calculated and compared. Figures 1 and 2 illustrate the results. Figures 1 and 2 indicate that none of the companies' return series follows a normal distribution. Moreover, the distributions of these companies have different degrees of left and right skewness. Therefore, it is also not true that the returns distribution is negatively skewed for all the technology companies in the US.

Table 3 shows the transition matrix of the skewness value before and during Covid. Table 3 indicates that the COVID19 pandemic changed the sign of skewness for 21 out of 34 US technology companies whilst 11 companies transferred from negative skewness to positive skewness and 10 companies transferred from positive skewness to negative skewness, which indicates that the COVID-19 pandemic had a significant impact on the skewness of the returns. Even though certain stocks experienced a large amount of change in terms of skewness, from the stock pool we selected, the ratio of the number of stocks that have left skewness to the number of stocks that have left skewness is roughly the same.

Table 3 Transition Matrix of Skewness Before and During Covid-19

	Skewness < 0 (During Covid)	**Skewness > 0 (During Covid)**
Skewness < 0 (Before Covid)	7	11
Skewness > 0 (Before Covid)	10	6

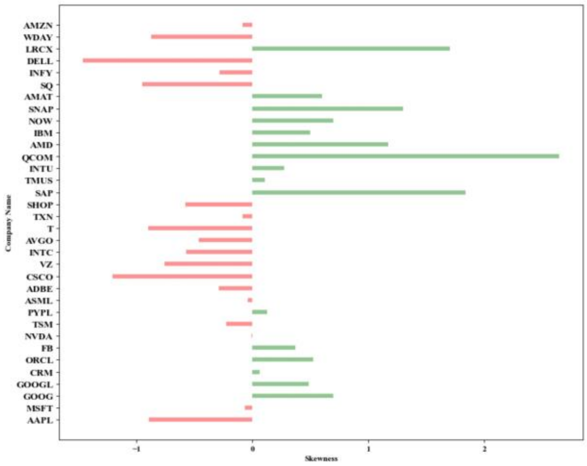

Fig. 1. Skewness before COVID.

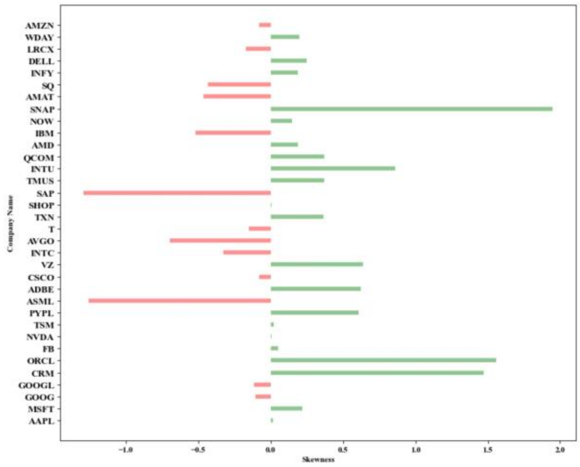

Fig. 2. Skewness during COVID.

3.4 Multivariate series of absolute returns show profound evidence of cross-correlations

Even though many stock returns are not correlated with each other, many researchers propose that multivariate series of absolute returns show profound evidence of cross-correlation. Cross-correlation measures the movements of two or more sets of time series data relative to one another. It is used to evaluate several time series and objectively assess how well they match up with each other and, in particular, at what moment the best match occurs. Statistically, cross-correlation is used to determine the similarities in the movement of several time series across time. Cross-correlation is used by investors and analysts to determine how two or more stocks—or other assets—perform against one another. Most often it is employed for transactions involving correlation, such as dispersion methods and pairs trading. Cross-correlation is also used in portfolio management to determine the diversity of the assets in a portfolio. It is important for investors to diversify their holdings to minimize the risk of large losses. For example, the prices of two technology stocks may move in the same direction most of the time, whereas the prices of a technology stock and an oil stock may move in different directions most of the time. Cross-correlation enables investors to pinpoint their movement patterns more accurately.

Figures 3 and 4 below shows the heatmap of cross-correlation of absolute returns before and during Covid.

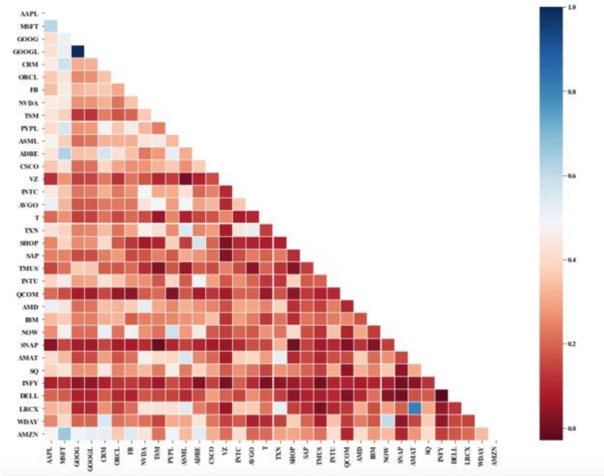

Fig. 3. Cross-correlation of absolute returns before Covid.

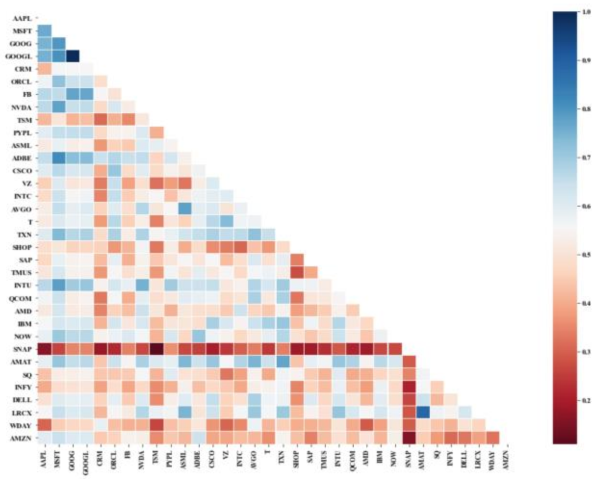

Fig. 4. Cross-correlation of absolute returns during Covid.

4 CONCLUSION

To conclude, this research determined whether the COVID19 pandemic altered statistical qualities and whether some stylized facts remained intact in the aftermath of COVID19 based on evidence from technology companies in the US. This research demonstrates that autocorrelation persists in the COVID-19 context, even though there was a lack of autocorrelation prior to this. Additionally, this research demonstrates that volatility clustering exists both before and during Covid and that the stock market is more volatile during Covid than it was before the pandemic. Besides, the research contradicts the conventional fact of negative skewness in return series, indicating that around 50% of businesses' return series exhibit positive skewness. The research also contradicts the fact that there is cross-correlation of absolute returns amongst multivariate series. In a nutshell, the COVID-19 pandemic did alter certain statistical qualities and investors may look for new investment opportunities due to these changes. Alternatively, they might adjust existing strategies to deal with the impact and changes brought about impact of the COVID-19 epidemic on the stock market.

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