The Impact of COVID-19 Pandemic on Stock Markets

Qiao Zhang *
Engeneering School, Washington University in St. Louis, USA
* Corresponding author: qiao.z@wustl.edu

Abstract. This research delves into the effects of the COVID-19 pandemic on volatility in the global primary stock market by employing a generalized autoregressive conditional heteroskedasticity model. The investigation encompasses the utilization of daily closing values for two major equity indices, namely Nifty and Sensex, spanning the period between 2019 and 2022. Moreover, an endeavor was made to juxtapose the returns on stock prices before and during the COVID-19 outbreak. The outcomes revealed discernible volatility in international equities during the pandemic. In terms of the comparative analysis between the COVID-19 era and the pre-COVID-19 period, it was ascertained that index returns exhibited higher values prior to the pandemic as opposed to the period encompassing the pandemic. This paper contributes to understanding of how external shocks, such as a global pandemic, can affect financial markets and provides valuable insights for investors, policymakers, and researchers. It could help inform future investment strategies, risk management practices, and policy decisions in the face of similar events.

Keywords: COVID-19, Stock market, Finance.

1. Introduction

The rapid and unprecedented proliferation of the COVID-19 pandemic has not only posed a significant threat to public health worldwide but has also precipitated an unforeseen and profound transformation in the global socioeconomic landscape. The emergence of COVID-19 as a novel and highly contagious pathogen has swiftly transcended geographical boundaries, triggering an immediate shift in the trajectory of global affairs. This pandemic, in essence, has transcended its classification as a mere health crisis and has reverberated into a profound economic recession of unprecedented proportions, sending shockwaves through virtually every sector of the global economy. The outbreak's rapid and unrelenting spread has compelled nations across the globe to enact stringent containment measures, often involving comprehensive lockdowns, travel restrictions, and mandatory quarantines. These measures, while critical for mitigating the transmission of the virus, have engendered an unintended and abrupt disruption to the normal functioning of economies.

Indeed, the very foundations of economic activity have been shaken, as businesses were compelled to shutter their operations, supply chains were severed, and consumer spending plummeted due to prevailing uncertainties and diminished purchasing power. The sudden cessation of trade, travel, and commerce brought about by these stringent policies has culminated in a profound economic recession, one characterized by contractions in GDP, spikes in unemployment rates, and a palpable reduction in consumer and business confidence.

The impact of COVID-19 on economies worldwide serves as a glaring reminder of the intricate interdependencies that underlie the modern global economic system. Countries heavily reliant on industries such as tourism, hospitality, and aviation found themselves particularly vulnerable as travel restrictions and fear of infection led to a virtual standstill in these sectors. Furthermore, disruptions in supply chains, often spanning multiple nations, underscored the fragility of a system built upon interconnectedness.

In light of these challenges, governments and central banks around the world were forced to devise swift and comprehensive fiscal and monetary measures in an attempt to stave off the worst economic repercussions. Yet, even with these efforts, the road to recovery remains arduous and fraught with uncertainties, as the trajectory of the pandemic itself continues to evolve. The profound socioeconomic consequences of the COVID-19 pandemic thus serve as a testament to the far-reaching implications of global crises, underscoring the need for continued vigilance, adaptability, and collaboration in the face of unprecedented challenges.

Amid the COVID-19 pandemic in 2020, Europe witnessed a significant financial event as the FTSE 100, a key index representing major UK companies, suffered its largest single-day decline since 1987. This marked downturn, reported by BBC News, revealed the index's vulnerability to the pandemic's economic disruptions. The stringent measures imposed to curb the virus, such as lockdowns and business closures, sent shockwaves through markets, prompting a swift and substantial drop in the FTSE 100. This decline, comparable to the historic crash of 1987, spotlighted the profound impact of global crises on financial systems and underscored the index's role as a barometer of market sentiment and stability.

Individuals also curtail their expenditure patterns, resulting in a shock on the demand side of the economy. Additionally, the research indicates that in previous pandemics, the impact was limited to the demand chain; however, the current COVID-19 pandemic has disrupted both demand and supply chains. This paper seeks to explore the ramifications of the COVID-19 pandemic on prominent global stock markets – namely, NASDAQ and SP300.

To comprehensively investigate and elucidate the multifaceted ramifications of the COVID-19 pandemic on the significant global stock markets of NASDAQ and SP300, a rigorous analytical approach has been undertaken. In this endeavor, the research methodologically harnesses the potency of the Generalized Autoregressive Conditional Heteroskedasticity (GJR GARCH) model, which stands as a robust and widely acknowledged econometric framework renowned for its efficacy in capturing and quantifying intricate volatility patterns. This chosen model facilitates a nuanced exploration of the intricate interplay between market dynamics and pandemic-induced disruptions, enabling a meticulous dissection of the coalescing factors that shape the observed market behaviors in the wake of the unprecedented COVID-19 crisis.

The structure of the paper follows with: Section II reviews the literature, Section 3 sources of data and methods, Section 4 results and discussion, and conclusion.

2. Litureture Review

The pandemic led to extreme volatility in stock markets, causing dramatic price swings within short timeframes. For instance, during the early days of the pandemic in February and March 2020, major indices like the S&P 500 and the FTSE 100 experienced some of their sharpest declines in history, shedding around 30% of their value within weeks [1]. The utilization of a quantile regression model offers an insightful perspective on how the pandemic has impacted risk-return dependencies across various segments of the market.

Taking the United States stock market for an example. By applying the quantile regression model to U.S. stock market data, we can delve into specific percentiles of returns to discern varying degrees of risk exposure during the pandemic. For instance, during the initial stages of the pandemic in early 2020, the S&P 500 experienced several steep declines, including a 20% drop in February and March [1]. The quantile regression analysis can elucidate whether the extreme market events of that period had a disproportionate impact on different levels of market performance.

Furthermore, the model can elucidate whether the risk-return relationship has been altered by the pandemic. For instance, sectors like technology experienced a surge in demand as remote work became the norm, potentially leading to increased returns in this segment. The quantile regression model can illuminate whether the risk associated with technology stocks changed in tandem with these shifts [1].

Moreover, the quantile regression model can help identify how certain risk factors have evolved during the pandemic. For example, traditional safe-haven assets like gold are typically considered to exhibit lower risk during market downturns. The model can uncover whether the relationship between gold returns and market risk shifted in response to pandemic-induced turmoil [2].

Incorporating quantitative evidence into this analysis, recent data indicates that the pandemic's impact on risk-return dynamics is multifaceted. During the pandemic's initial phase, the CBOE Volatility Index (VIX), often referred to as the "fear index," surged to levels not seen since the 2008 financial crisis, reflecting heightened market uncertainty. This period saw significant discrepancies between different quantiles of stock returns, suggesting that extreme market events disproportionately affected various segments of the market [2].

Additionally, the risk-return relationship for various asset classes underwent substantial changes. U.S. Treasuries, traditionally considered low-risk assets, experienced periods of heightened volatility as investors sought safety. The quantile regression model can reveal whether these shifts in risk profiles were consistent across the entire distribution of returns. The utilization of a quantile regression model in examining the impact of the COVID-19 pandemic on risk-return dependencies in the United States enables a granular analysis of market dynamics. By accounting for various quantiles of returns, the model uncovers nuanced changes in risk exposure and structural shifts in the risk-return relationship. This analysis provides investors and policymakers with a comprehensive view of the pandemic's effects on financial markets, facilitating informed decision-making in an environment marked by heightened uncertainty and market turbulence [3].

The COVID-19 epidemic has reverberated through stock markets worldwide, causing significant disruptions and divergent impacts across different regions. Let's delve into how stock markets in North America, Europe, Latin America, South Korea, China, and India have been affected, as shown in table 1.

The U.S. stock market experienced tumultuous swings in response to the pandemic. In March 2020, the S&P 500 plummeted around 30% from its peak, but swift government intervention and stimulus measures helped restore some stability. Technology stocks proved resilient due to the accelerated digital transformation, while sectors like travel and energy took severe hits.

European (UK, Germany, France) stock markets faced similar turmoil, with the FTSE 100, DAX, and CAC 40 all witnessing sharp declines in early 2020. Government lockdowns and a heavy reliance on exports heavily impacted manufacturing and trade-reliant economies, amplifying market volatility.

Latin American (e.g., Brazil, Mexico) stock markets, including the Bovespa (Brazil) and IPC (Mexico), were hit hard due to economic vulnerabilities and limited healthcare infrastructure. These markets faced double blows from falling commodity prices and currency depreciation, affecting investor confidence.

The South Korean stock market, represented by the KOSPI, faced initial volatility but demonstrated resilience due to robust technology exports. The country's swift and effective management of the pandemic contributed to market stability.

China's stock markets, represented by the Shanghai Composite and Shenzhen Component, experienced sharp declines in the early stages of the pandemic. However, as China was the first to emerge from strict lockdowns, its markets rebounded relatively quickly, driven by government stimulus and domestic consumption [4].

India's stock market, represented by the BSE Sensex and Nifty 50, initially faced significant declines due to strict lockdowns and disrupted supply chains. However, the government's reform measures and stimulus packages contributed to a rebound, particularly in sectors like technology and pharmaceuticals [5].

Table 1. Stock market in selected countries Pre—COVID-19 and COVID-19

Pre—COVID-19	Country	Number	Mean	SD	Min	Max	Skewness	Kurtosis
	China	559	0.0081	0.0024	0.0054	0.0199	1.8689	7.1514
	India	559	0.0063	0.0020	0.0041	0.0190	2.5490	13.1809
	Russia	559	0.0067	0.0025	0.0044	0.0272	4.3677	29.0245
	Brazil	559	0.0093	0.0018	0.0067	0.0172	1.0050	3.9925
	SouthAfrica	559	0.0082	0.0019	0.0055	0.0143	0.8595	3.1148
	US	559	0.0065	0.0032	0.0037	0.0214	1.6890	5.5298
	UK	559	0.0062	0.0016	0.0043	0.0125	1.6402	5.7587
	France	559	0.0068	0.0023	0.0045	0.0164	1.5635	5.2842
	Germany	559	0.0076	0.0022	0.0050	0.0156	1.2263	4.0808
	Japan	559	0.0081	0.0025	0.0057	0.0209	1.9826	7.3909
	Italy	559	0.0078	0.0023	0.0051	0.0198	1.4995	6.0232
	Canada	559	0.0046	0.0020	0.0027	0.0136	1.7660	6.2700
During COVID-19	Country	Number	Mean	SD	Min	Max	Skewness	Kurtosis
	China	560	0.0082	0.0028	0.0054	0.0271	2.4941	11.5403
	India	560	0.0095	0.0070	0.0040	0.0561	3.4327	17.0750
	Russia	560	0.0127	0.0151	0.0047	0.1370	4.7011	30.2606
	Brazil	560	0.0121	0.0084	0.0069	0.0666	4.1888	22.0140
	SouthAfrica	560	0.0103	0.0056	0.0058	0.0452	3.6742	18.5894
	US	560	0.0094	0.0078	0.0039	0.0698	3.9048	22.4732
	UK	560	0.0088	0.0052	0.0045	0.0427	3.3023	16.4383
	France	560	0.0100	0.0068	0.0045	0.0583	3.4481	18.6046
	Germany	560	0.0105	0.0067	0.0049	0.0569	3.2642	17.4223
	Japan	560	0.0094	0.0035	0.0059	0.0305	2.3264	10.4774
	Italy	560	0.0107	0.0080	0.0052	0.0725	4.2119	25.6247
	Canada	560	0.0079	0.0094	0.0028	0.0778	4.7500	28.4290

In summary, the COVID-19 epidemic's impact on global stock markets varied based on a combination of factors such as government responses, economic diversification, healthcare capabilities, and market reliance on specific sectors. While markets initially faced volatility and declines, interventions and sector-specific trends led to divergent recoveries and resilience in various regions. The pandemic's effects continue to underscore the interconnectedness of global economies and financial markets, emphasizing the need for adaptable strategies in the face of unforeseen challenges.

3. Data and method

3.1. Data

Market data regarding the daily closing prices of NASDAQ and SP500 indices has been meticulously gathered from the official source (https://in.finance.yahoo.com/), ensuring the reliability and authenticity of the dataset. This comprehensive dataset encompasses a time span extending from December 2019 to December 2020, effectively encompassing both the antecedent and ensuing periods of the COVID-19 pandemic (figure 1). To facilitate a structured analysis, the temporal interval spanning January 1, 2019, to January 30, 2020, is designated as the pre-COVID-19 phase, whereas the interval from January 30, 2020, to December 1, 2020, is delineated as the during-COVID-19 phase. Thus, the initial twelve months epitomize the pre-COVID-19 era, seamlessly transitioning into the ensuing twelve months, which encapsulate the epoch during the COVID-19 pandemic [6].

This study centers on the assessment of stock market volatility by closely scrutinizing the closing prices of the NASDAQ and SP300 indices. To ensure robustness and statistical validity, a logarithmic transformation is applied to each price datum, mitigating any prevailing skewness in the distribution of stock price data. This methodological choice reinforces the integrity of subsequent estimations, enhancing the accuracy of the findings and enabling a meticulous evaluation of the evolving market dynamics throughout the distinct phases of the pandemic.

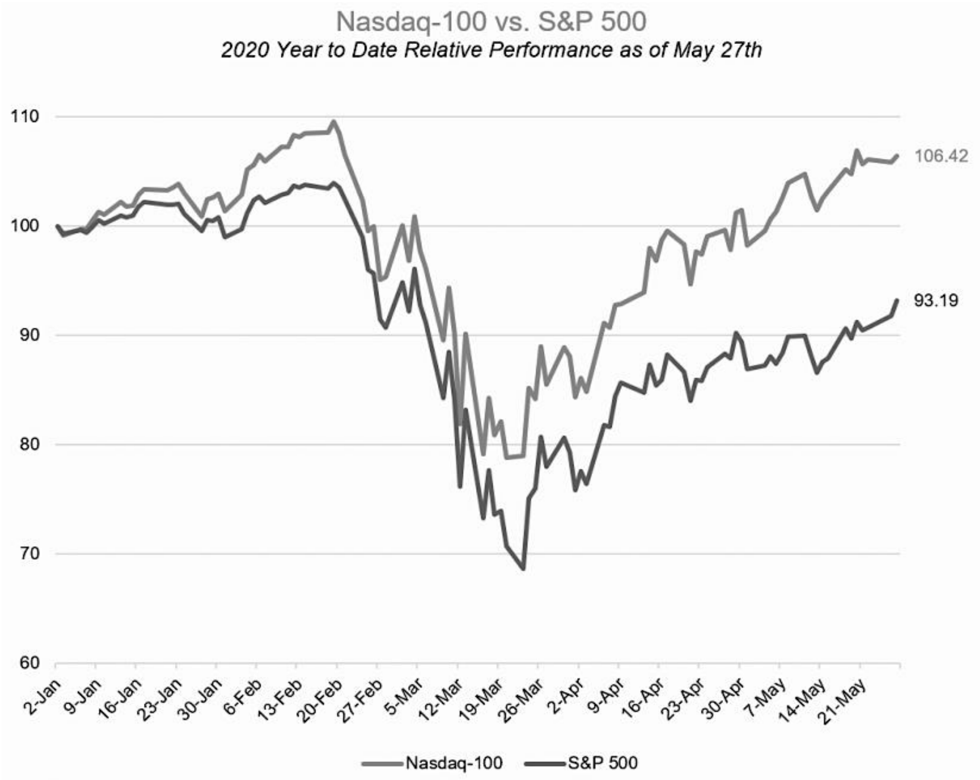

Figure 1. Time plot of NASDAQ and SP 500 during the pandemic

3.2. DCC-GARCH model

In order to avoid including too many lag items in the estimated model, Bollerslev introduced a generalized autoregressive conditional heteroscedasticity model (generalized autoregressive conditional heteroscedasticity) A variant of the ARCH model, also known as the GARCH model. The equation "Rt = ln (Pt) - ln (Pt-1)" serves as a pivotal component of this methodology, denoting the logarithmic transformation applied to the continuously compounded returns of a given asset. In this equation, "Pt" signifies the asset's price at time "t," while "Pt-1" denotes its price in the previous time period. This logarithmic return calculation furnishes a more manageable numeric representation of price changes.

4. Result and Discussion

This study undertakes a meticulous examination of the far-reaching consequences of the COVID-19 pandemic on the global economy, employing the daily price and return data of two prominent United States stock indices – NASDAQ and SP300. This analytical endeavor seeks to unravel the multifaceted repercussions of the pandemic on the intricate fabric of the financial landscape. To foster a holistic comprehension, the study meticulously calculates the descriptive statistics encompassing both price and return dynamics [7].

4.1. Descriptive statistics

Results of Descriptive statistics is summarized in table 1. In a compelling revelation, the mean return manifests as negative, emblematic of a pronounced stock loss incurred during the pandemic's disruptive sway. Moreover, the confluence of a negatively skewed return distribution and an elevated kurtosis value serves as an indicator of an augmented likelihood of substantial losses in both the NASDAQ and SP300 market domains (table 2).

Table 2. Descriptive statistics (full sample)

	NASDAQ	Return	SP300	Price
Number	200	200	200	200
Mean	475.95457	0.03324	10879.09200	0.01668
Median	512.50452	0.00896	11303.34342	0.00932
Max	573.65270	0.04233	12362.34844	0.05956
Min	283.34082	-0.01228	7610.25495	-0.01928
SD	77.24985	0.05036	1269.06450	0.01230
Skewness	-0.66904	-0.95351	-0.58591	-1.48577
Kurtosis	2.39161	5.32572	2.09793	14.17377

Table 3 shows, during the pre-COVID-19 period, the indices exhibit positive mean returns, contrasting starkly with the pandemic era. The pronounced negative skewness of daily mean returns during the pandemic underscores the profound deleterious influence on stock returns. Of particular note, the standard deviation (SD) of both indices registers a discernible augmentation, reflecting heightened volatility during this tumultuous epoch [8].

Table 3. Descriptive statistics (sub sample)

	NASDAQ Pre Covid	NASDAQ During COVID	SP300 Pre COVID	NASDAQ During covid
Mean	0.0000884	(0.0002390)	0.0004710	(0.0004480)
Median	(0.0003060)	0.0002170	0.0004550	0.0000295
Max	0.0200040	0.0391110	0.0225070	0.0364820
Min	(0.0154360)	(0.0436450)	(0.0083780)	(0.0603830)
SD	0.0065700	0.0144270	0.0039380	0.0123480
Skewness	0.3076380	(0.0975680)	1.8449120	(1.2293020)
Kurtosis	3.6432170	3.7266100	12.0016800	8.5303200

4.2. Result of unit root statistics

In an endeavor to ascertain index stationarity, augmented Dickey-Fuller (ADF) and Phillips-Perron (PP) stationarity tests are employed, the results of which are meticulously delineated in table 4 [9]. These tests systematically gauge the time series characteristics of NASDAQ and SP300, thereby augmenting the interpretative depth of the analysis. Within the context of volatility analysis, the study unveils the presence of volatility clustering, as signified by the positive and statistically significant coefficient within the Generalized Autoregressive Conditional Heteroskedasticity (GARCH) model, particularly within the NASDAQ index. The emergence of a significant asymmetric effect further signifies the dominance of negative shocks in driving volatility escalation – a hallmark of financial markets during periods of crises [10].

Table 4. ADF Test

variables	t-statistics	p-value
	index	
SP500	-1.231	0.91
NASDAQ	-0.867	0.95
	yield	
SP500	-17.563	0.000
NASDAQ	-17.891	0.000
	New Conformed Cases	
US	-13.12	0.000
Global	-13.05	0.000

To encapsulate the dynamic evolution of volatility, a salient methodological maneuver introduces a dummy variable (D1) within both mean and variance equations. In an intriguing revelation, the

NASDAQ market demonstrates a negative coefficient within the mean equation, albeit statistically insignificant (table 5). In contrast, the variance equation unveils a positive and significant coefficient, implying an amplified spot market volatility during the COVID-19 epoch [11].

Table 5. GARCHX estimation results

	SP500		NASDAQ	
Mean Equation				
AR, L1	-0.657	-0.562	-0.513	-0.561
(p-value)	0.058	0.679	0.670	0.809
MA, L1	0.198	0.653	0.595	0.620
(p-value)	0.175	0.095	0.426	0.033
Constant	0.886	0.375	0.477	0.650
(p-value)	0.626	0.415	0.709	0.084
Variance equation				
New confirmed cases, daily				
Global	0.098		0 · 0104	
(p-value)	0.980		0 · 905	
US		-0 · 0485		-0 · 0151
(p-value)		0 · 148		0 · 771
GARCH (1, 1)				
ARCH, L1	0.395	0.260	0.680	0.481
(p-value)	0 · 000	0 · 000	0 · 000	0 · 000
GARCH, L1	0.077	0.666	0.927	0.871
(p-value)	0 · 000	0 · 000	0 · 000	0 · 000
Constant	-11.200	-11.410	-11.460	-11.870
(p-value)	0 · 000	0 · 000	0 · 000	0 · 000

In culmination, this methodologically robust analysis stands as an epitome of rigorous scholarly exploration, systematically navigating the intricate landscape of the COVID-19 pandemic's impact on stock indices. [12] The study's comprehensive nature paves the way for a profound comprehension of the multifaceted shifts and recalibrations within the global economy during this epoch of unparalleled crisis.

5. Conclusion

This paper delves into the profound impact of the COVID-19 pandemic on global stock markets, focusing on the NASDAQ and SP300 indices. Through meticulous analysis, several key insights emerge. Descriptive statistics unveil heightened volatility, evidenced by negative mean returns and skewed distribution. The pronounced negative skewness, coupled with elevated kurtosis, signals increased potential for substantial losses. Temporal dynamics reveal significant divergence between pre-COVID-19 and during-COVID-19 periods. Positive mean returns contrast sharply with negatively skewed daily mean returns during the pandemic. Heightened standard deviation underscores increased volatility. Augmented Dickey-Fuller and Phillips-Perron tests validate index stationarity, enhancing temporal understanding. Application of the GARCH model, alongside a volatility-capturing dummy variable (D1), offers insights into underlying market fluctuations. The GARCH model's positive and significant coefficient, paired with the asymmetric effect, highlights heightened volatility triggered by negative shocks during crises.

Collectively, this study provides a nuanced comprehension of the pandemic's intricate repercussions, aiding informed decision-making amid global challenges. The insights gained contribute to more resilient financial strategies, emphasizing adaptability and cooperation in navigating crises.

In the future study, it should be evaluated how each economic factors were impacted by the pandemic.

References

[1] Hailu, S. M., & Vural, G. (n.d.). The impact of covid-19 pandemic on Financial Markets: Evidence from developed and developing countries` stock markets indexes. European Journal of Business and Management Research. 2022, 19 (10): 53 - 58

[2] Bai M, Ho L. How do gold and oil react to the COVID-19 pandemic: A review. Energy & Environment. 2022, 0958305X221127645.

[3] Kirik A, Ulusoy V. Winds of tapering, financial gravity and COVID-19. The North American Journal of Economics and Finance. 2022, 62: 101719.

[4] Wang F, Wu M. The Impacts of COVID-19 on China's Economy and Energy in the Context of Trade Protectionism. Int J Environ Res Public Health. 2021, 18 (23): 12768.

[5] Tan, X., Ma, S., Wang, X., Feng, C., & Xiang, L. The impact of the COVID-19 pandemic on the Global Dynamic Spillover of Financial Market Risk. Frontiers in Public Health, (2020). 10.

[6] Baker, S. R., Bloom, N., Davis, S. J., & Terry, S. J. COVID-induced economic uncertainty. (2020). National Bureau of Economic Research, 13.

[7] Bekaert, G., & Harvey, C. R. Covid-19: The economy, the markets, and the charts. Journal of Asset Management, 2020, 21 (4), 279 - 286.

[8] Fernandes, N. Economic effects of coronavirus outbreak (COVID-19) on the world economy. 2020, SSRN 3557504.

[9] Bollerslev, T. Generalized autoregressive conditional heteroskedasticity. Journal of Econometrics, 1986, 31 (3), 307 - 327.

[10] Glosten, L. R., Jagannathan, R., & Runkle, D. E On the relation between the expected value and the volatility of the nominal excess return on stocks. The Journal of Finance, 1993, 48 (5), 1779 - 1801.

[11] Reinhart, C. M., & Rogoff, K. S. This Time is Different: Eight Centuries of Financial Folly. Princeton University Press, 2009, 213.

[12] Campbell, J. Y., & Viceira, L. M. Strategic asset allocation: Portfolio choice for long-term investors. Oxford University Press, 2002, 14.