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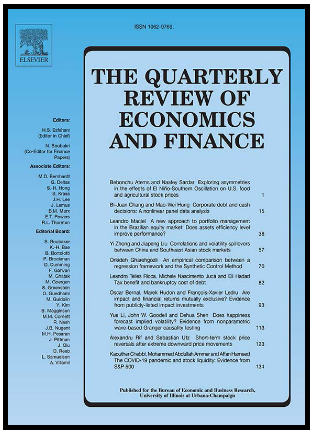

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The role of the COVID-19 pandemic in US market volatility: Evidence from the VIX index

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ABSTRACT

We examine how the implied volatility in the US financial market has been affected by the COVID-19 pandemic. We decompose the Chicago Board Options Exchange (CBOE) Volatility Index (VIX) into two implied volatility conditions (i.e., low and high), and COVID-19 pandemic cases and deaths into two categories (i.e., low and high). Our novel quantile-on-quantile regression approach allows us to better examine the dynamic relationship between the COVID-19 pandemic and implied volatility. Our empirical results show that increased death rates tend to increase fear in the US financial market. Specifically. we find that high COVID-19 cases have a significant impact on implied volatility under high uncertainty conditions, but low COVID-19 cases appear to have no impact on implied volatility in the US market. Our findings offer support to the US policy response by the Federal Reserve Board and the government to limit the instability effect of the COVID-19 shock on the financial markets.

Keywords: VIX; COVID-19; quantile-on-quantile regression; forecasting

JEL Classification: G11; C32

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1. Introduction

The end of the year 2019 saw the outbreak of a novel respiratory disease (COVID-19) that plunged the entire world into a pandemic. By the end of March 2022, there were more than 474 million confirmed cases across 237 countries. In the United States (US) alone, there were 81 million cases and 966,570 deaths on March 25, 2022[1]. The US economy suffered one of the sharpest contractions in its history during 2020 (i.e., GDP fell by 29.9 percent in the second quarter of 2020)[2]. Initial forecasts by the International Monetary Fund (IMF) warned that the world economy is expected to experience the worst recession since the Great Depression of the 1930s (Gopinath, 2020), and by the end of 2020, global economic growth fell by -3.1 percent, although it was expected to accelerate to 5.9% in 2021 (IMF, 2021). In a more recent forecast, the IMF predicted the world output growth to slow from 4.4% in 2022 to 3.8% in 2023. The report also commented that the strong rebound is easing due to rising energy prices, supply chain disruptions, inflation, and the emergence of the Omicron variant (IMF, 2022).

The COVID-19 pandemic caused fear among investors, creating stock market plunges and volatility spikes in the US equity and options markets. Without a doubt, it

[1] https://covid19.who.int/
[2] https://fred.stlouisfed.org/series/A191RL1Q225SBEA [accessed on December 24, 2022]

generated turbulence in the global financial markets (John and Li, 2021). The Standards and Poor's (S&P) 500 index experienced a historic plunge by losing one-third of its value between February 20 and March 23, 2020 (Capelle-Blancard and Desroziers, 2020). Likewise, the pandemic has led to the highest rise in the history of the Chicago Board Options Exchange (CBOE) Volatility Index (VIX), which measures implied volatility. The VIX index reached 83 units on March 16, 2020, while the index was held at between 12 to 15 points prior to the pandemic (Raheem, 2021). An increase in implied volatility, as measured by VIX, can be gauged as a reflection of global uncertainty, leading to a decrease in the risk appetite of investors and risk aversion in the global capital markets (Byrne and Fiess, 2016).

The outbreak of the COVID-19 pandemic has caused a shock to the financial systems, causing uncertainty and systematic risk. A growing number of researchers have been quick to recognize the need to explore the effects of the pandemic on the global financial systems. For instance, Caggiano et al. (2020) use the VAR approach to estimate the effects of an uncertainty shock related to a COVID-19 outbreak (i.e., the one that occurred in March 2020), predicting a peak negative response of world industrial production of 1.6% and a cumulative loss over one year of about 14%. Using graphical analysis, Altig et al. (2020) assess a handful of forward-looking uncertainty measures for the United Kingdom (UK) and US prior to and after the COVID-19 pandemic. Their analysis of all measures (i.e., implied stock market volatility, newspaper-based policy uncertainty, and Twitter chatter about economic uncertainty) suggests that the COVID-19 pandemic led to record-high levels of economic uncertainty. Building on Altig et al. (2020) study, Barrero and Bloom (2020) find that the COVID-19 pandemic has caused a large fear of negative tail-risk (i.e., extreme risk) outcomes, in addition to economic uncertainty across the UK and the US firms.

We contribute to the burgeoning literature on the impact of the COVID-19 pandemic on volatility in the financial markets. Given the importance of volatility to the performance of stock markets, it is unsurprising that recent studies have focused on the impact of the COVID-19 pandemic on stock market returns or the volatility in stock returns (Ali et al., 2020; Cepoi, 2020; Erdem, 2020; Salisu and Vo, 2020). Rather more surprisingly, scant research has focused on the impact of the COVID-19 pandemic on implied volatility using the VIX index.

Relatedly, Albulescu (2020) illustrates that the COVID-19 death ratio leads to an increase in financial volatility (the VIX index). However, this study is based on a very limited data at the early stage of the COVID-19 pandemic (i.e., 40 days after the start of the international monitoring of the pandemic). Using panel data analysis, Papadamou et al. (2020) examine the impact of the COVID-19 pandemic on implied volatility in 13 countries (i.e., from the US, Europe, and Asia). The authors use a Google-based measure to quantify anxiety about COVID-19 contagion effects and document that the COVID-19 pandemic led to a positive impact on implied volatility, therefore causing elevated risk aversion in stock markets. Conversely, Just and Echaust (2020) use the two-regime Markov switching model and a sample of 12 countries (including the US) and document that it is only in Italy that the COVID-19 pandemic (cases/deaths) has a positive impact on implied volatility (the VIX index). The authors suggest that this is because Italy was the first country in Europe to experience the pandemic and it was, at that time, the hardest hit.

Using simple OLS regressions, Albulescu (2021) provides robust evidence that the COVID-19 pandemic has a clear positive impact on S&P500 realized volatility. While the sample period of this study is limited, covering the early days of the outbreak (i.e., March 11, 2020 to May 15, 2020), we agree with his analytical perspective. Hence, we use the Quantile-on-Quantile Regression (QQR)[3] method to better examine the dynamic relationship between two different categories of the COVID-19 pandemic and two levels of implied volatility. Also, we cover extended COVID-19 period (i.e., March 3, 2020 to February 26, 2021) to analyze the possibility of COVID-19 pandemic impacting implied volatility and the associated risk in a longer period using QQR approach.

In this paper, our goal is to study how the implied volatility in the US financial market was affected by the COVID-19 pandemic over the period March 3, 2020 through February 26, 2021. Given the consequences of the COVID-19 pandemic on financial markets, the intuition is that market fear will be reflected in the levels and movements of market volatility measures (John and Li, 2021). The analysis uses VIX, which is well known to market participants as Wall Street's "fear gauge" or "fear index". The index is based on out-of-money put and call S&P500 index options prices (John and Li, 2021; Whaley, 2000; Andersen et al., 2003). The literature has examined implied volatility by mainly using the VIX index because it has important implications for the operation of financial markets. Implied volatility contains information about future volatility (Fassas and Siriopoulos, 2021) and coincides with market turmoil (Whaley, 2000). It is used in Value-at-Risk calculations (Slim et al., 2020), and the valuation of Credit Default Swaps (CDS) (Cao et al., 2010). It reflects investors' sentiment and is associated with stock market returns (Whaley, 2000; Simon, 2003; Baker and Wurgler, 2006).

[3] Our novel QQR approach is important – please see advantages of QQR method on page 8.

This paper has two primary contributions. First, we extend the existing literature (e.g., Albulescu, 2021; Just and Echaust, 2020) by proposing a novel QQR approach to test the dynamic relationship between the COVID-19 pandemic and implied volatility. More specifically, we decompose the options-based VIX index into two implied volatility conditions (i.e., low and high) and the COVID-19 pandemic event into two categories (i.e., low and high) for cases and deaths. To the authors knowledge, this is the first study to examine the relationship between investor fear proxied by the VIX and the COVID-19 pandemic by reference to VIX conditions (i.e., low and high), and COVID-19 cases and deaths (i.e., low and high). Given that linear modelling cannot capture the fat tails exhibited by leptokurtic distribution, and nor can it capture the asymmetry exhibited by the measure of skewness in asset returns, the econometric approach we follow, utilizing quantile regressions, overcomes such limitations. Importantly, the effect of independent variables, such as the COVID-19 pandemic, can give robust results irrespective of distributional assumptions. In addition, our methodology is appropriate since the results show that risk sensitivities to the pandemic event differ across quantiles, implying that risk exposures vary under different risk conditions (Badshah, 2013). We add depth to the literature by covering a more extensive period of the COVID-19 pandemic, as prior studies have mostly been limited to the early period of the virus (Albulescu, 2020; Albulescu, 2021; Just and Echaust, 2020).

Second, our analysis for the first time captures how market participants perceive jump-tail risks, i.e., the risk of rare, albeit disruptive, events, and how they react to a financial crisis and a rare disaster, such as the COVID-19 pandemic (Pukthuanthong and Roll, 2015; Zhang et al., 2022). Market participants' perceptions of tail risk may hinder the economic recovery from large shocks, such as the COVID-

19 pandemic shock, or even weigh on long-term growth prospects. At the same time, insuring against tail risks has potentially significant macroeconomic and financial implications. For example, going from a low to a high level of risk insurance changes the equilibrium valuation of assets. Furthermore, any changes in asset pricing translate, in turn, to an equilibrium adjustment in relative wealth and demand, possibly leading to the re-allocation of labour and production across regions/countries (Mankiw, 1986; Wachter, 2013; Tsai and Wachter, 2016; Borovicka and Borovickova, 2018). Tail risks are also considered predictors for returns/excess returns (premiums) (Goyal and Welch, 2008; Chevapatrakul et al., 2019), and thus are capable of forecasting excess market returns at various investment horizons. Given that tail risks are predominantly associated with extreme negative events (i.e., in our particular case, the pandemic crises), it is plausible that financial markets' reaction to tail risks is asymmetric. Therefore, the impact of tail risks on stock returns is expected to vary depending on whether the market is bullish (i.e., when the excess return is highly positive) or bearish (i.e., when the excess return is highly negative).

Furthermore, the Global Financial Crisis of 2007-2008 (GFC) had significant negative effects on financial markets and macroeconomic indicators across countries (Eichengreen and O'Rourke, 2009). It is now well documented that the impact of the COVID-19 pandemic on the stock market has been significantly strong and unprecedented compared to previous outbreaks of infectious disease (i.e., including the Spanish flu) (Baker et al., 2020). Bollerslev and Todorov (2011) document that the financial markets incorporate rare events, such as GFC, in a fashion similar to the pricing of risky payoffs. Investor fear of such unfortunate events accounts for a large fraction of the historically observed average equity and variance risk premia. The empirical findings implicitly highlight that policymakers must decrease uncertainty by removing tail risks and lessening the perception of jump tail risk if they are to restore asset values during a crisis. In relation to the COVID-19 pandemic, the events of the first quarter of 2020 help us to gauge how financial markets process and respond to the unprecedented challenges posed by a disaster.

Certain recent studies have explicitly analyzed the realized volatility in the stock market (Ali *et al*., 2020; Bai *et al*., 2020; Baker *et al*., 2020; Erdem 2020; Mazur *et al*., 2021; Zhang *et al*., 2020). Drechsler and Yaron (2011) argue that derivatives markets are particularly appropriate contexts for disentangling the connection between uncertainty and prices where volatility plays a conspicuous role. They argue that the derivative markets provide great scope for understanding how perceptions of economic uncertainty and cash flow risks feed into asset pricing.

Our empirical results indicate that increased death rates tend to increase fear across financial markets. We document that high COVID-19 cases have a significant positive impact on implied volatility under high uncertainty conditions. We also show that low numbers of COVID-19 cases do not affect implied volatility in the US market. Our results offer support for the US policy response by the Federal Reserve Board and the government to limit the instability effect of the COVID-19 shock on financial markets. Notably, the Federal Reserve Board stepped in to promote financial stability by lowering the federal funds rate to a range of 0% to 0.25% and made large purchases of US government and mortgage-backed securities[4]. The federal government spent $7.49 trillion (i.e., 31% of the GDP) in 2020[5]. These fiscal expenditures were made to directly support firms, households, workers, as well as State and local governments. As a result of the successful policies, the U.S. economic

[4] https://www.brookings.edu/research/fed-response-to-covid19/ [accessed on December 24, 2022]

[5] https://fiscaldata.treasury.gov/americas-finance-guide/federal-spending/ [accessed on December 24, 2022]

recovery from COVID-19 has been remarkably fast, with a GDP growth of 5.7 percent in 2021[6].

The remainder of the paper is organized as follows. Section 2 presents data and methodology. Section 3 presents the empirical results and a discussion of the findings. Section 4 provides the concluding remarks.

2. Methodology and data

The objective of this paper is to examine the effects of the COVID-19 pandemic on the implied volatility in the US stock market. The empirical analysis uses the QQR method developed by Sim and Zhou (2015). This method allows for the capture of the dynamic connection between VIX and COVID-19 in different VIX conditions (i.e., low and high) and varying levels of COVID-19 (i.e., low and high), whether the levels are measured as cases or deaths. In the cases of VIX nonlinearities, values of the VIX located in the upper quantiles may substantially reflect cases of a severe crisis that are followed by tremendous declines in stock returns, as well as aggressive interest rate cuts that are due to a collapse in real activity, reflecting changes in cash flow expectations (Campbell et al., 2013).

The QQR is a generalization of the standard quantile regression approach, which can examine how the quantiles of a variable affect the conditional quantiles of another variable (Sim and Zhou, 2015). This method helps to assess the entire dependence structure of VIX and COVID-19 measures by using their intrinsic information. Specifically, by using the QQR, the analysis can model the quantile of VIX volatility as a function of the quantile of COVID-19 (COVID19), so that the link between them can vary at each point of their respective distributions.

[6] https://home.treasury.gov/news/featured-stories/measuring-the-strength-of-the-recovery [accessed on December 24, 2022]

If θ denotes the quantile of VIX, then the analysis postulates a model for the θ-quantile of VIX as a function of COVID19, the lagged VIX, and a vector of other potential determinants of VIX. The VIX determinants include volume, trading/transaction costs, market conditions (Fleming et al., 1996; Chakravarty et al., 2004), VIX futures (Frijns et al., 2016; Chen and Tsai, 2017), and the COVID-19 pandemic. Using Equation (1), the model yields:

$$VIX_t = \beta_0 + \beta^{\theta}\ \Delta COVID19_t + \alpha^{\theta}\ VIX_{t-1} + a\ \Delta X_t' + \varepsilon_t^{\theta} \quad (1)$$

where ε_t^{θ} is an error term that has a zero θ-quantile, β_0 is a constant term, and X_t is a vector of control variables. The QQR method allows the relationship function β^{θ} (.) to be unknown, as it does not have any prior information for how VIX and COVID19 are associated. To examine the dependence structure between the quantile of VIX and the quantile of COVID19 denoted as $COVID19^{\tau}$, it linearizes the function β^{θ} (.) by considering the first-order Taylor expansion of β^{θ} (.) around $COVID19^{\tau}$, which yields the following:

$$\beta^{\theta}\ \Delta COVID19_t = \beta^{\theta}\ \Delta COVID19^{\tau} + \beta^{\theta'}\ (\Delta COVID19^{\tau})\ (\Delta COVID19_t - \Delta COVID19^{\tau}) \quad (2)$$

Given that Sim and Zhou (2015) define β^{θ} $COVID19^{\tau}$ and $\beta^{\theta'}$ $COVID19^{\tau}$ as $\beta_0(\theta,\tau)$ and $\beta_1(\theta,\tau)$ respectively, then Equation (3) can be estimated as follows:

$$\beta^{\theta}\ \Delta COVID19_t = \beta_0(\theta,\tau) + \beta_1(\theta,\tau)\ (\Delta COVID19_t - \Delta COVID19^{\tau}) \quad (3)$$

We substitute Equation (3) into Equation (1), which yields the following:

$$VIX_t = \beta_0(\theta,\tau) + \alpha(\theta)\ VIX_{t-1} + a\ \Delta X_t' + \beta_1(\theta,\tau)\ (\Delta COVID19_t - \Delta COVID19^{\tau}) + \eta_t^{\theta} \quad (4)$$

where $\alpha^{\theta} = \alpha(\theta)$. The expression $\beta_0(\theta,\tau) + \beta_1(\theta,\tau)\ (\Delta COVID19_t - \Delta COVID19^{\tau})$ considers the linkage between the θ-quantile of VIX and the τ-quantile of ΔCOVID19, given that β_0 and β_1 are doubly indexed in θ and τ.

We use the CBOE VIX index as the dependent variable in our regressions. The VIX level at any point allows us to form expectations for the future path of actual volatility. More specifically, the VIX level at any point may be naively interpreted as a prediction for the annualized level of realized volatility over the next 30 days (Edwards and Preston, 2017).

The relationship between VIX and trading volume is explained by two theoretical hypotheses: first, the mixture of distribution hypothesis (Andersen, 1996) which indicates that market returns are not drawn from a single probability distribution, but rather from a mixture of conditional distributions with varying degrees of efficiency in generating the expected returns. This mix determines the information arriving at the market and explains the presence of volatility/uncertainty effects in asset price movements. Second, the sequential information arrival hypothesis (Copeland, 1976; Jennings et al., 1981; Smirlock and Starks, 1988) assumes that information is disseminated asymmetrically. New information is disseminated sequentially to the market participants, and uninformed participants are not aware of the presence of informed participants. The latter takes positions and adjust their portfolios accordingly, resulting in a series of sequential equilibria before a final equilibrium is attained. This sequential dissemination of information correlates with the number of transactions. Thus, any new arrival of information to the markets results in a rise in trading volume, with a positive link between volume and VIX. Furthermore, the inclusion of transaction costs is justified because they determine the profitability of VIX-based trading strategies (Lynch and Balduzzi, 2000). Their link is also expected to be positive. The inclusion of VIX futures is justified because investment exposure to the index is achieved principally by trading VIX futures. The expectations hypothesis, which is based on the risk-neutral formulation hypothesis proposed by Campa and Chang (1995), suggests that the information content of futures markets is an important component of any empirical work involving the VIX. Once again, their association is expected to be positive. Finally, the negative nexus between the VIX index and market conditions (i.e., S&P500 prices) captures the leverage effect first discussed by Black (1976).

Trading/transaction costs are measured as the relative spread; this is defined as the daily average value of the difference between ask and bid quotes on prices relative to the quote midpoint. The volume-related metric is the trading volume, calculated on a daily basis. The analysis uses S&P500 prices as a proxy for market conditions. It also includes VIX futures, i.e., exchange-traded futures contracts on volatility that are used to trade and hedge volatility. The underlying asset of these contracts is VIX. The VIX futures contracts are cash-settled. The final settlement date is the Wednesday thirty days prior to the third Friday of the calendar month that immediately follows the month in which the contract expires.

We use a daily dataset from 03-03-2020 to 26-2-2021. We use four indicators for the COVID-19 pandemic: i) total confirmed cases in the US, ii) the number of death cases in the US, iii) total worldwide confirmed cases, and iv) the number of death cases worldwide. All data are obtained from Refinitv Datastream.

3. Empirical analysis

Table 1 provides descriptive statistics. To visualize the trend of our data series, we plot the four alternative indicators of the COVID-19 pandemic and the VIX index in Figures 1, 2, and 3. Implied volatility skyrocketed to the highest level ever recorded by CBOE VIX on Monday, March 16, 2020; this surge followed the declaration of a national emergency by the US President on Friday, March 13, 2020 (Table 1 and Figure 1). Notably, this spike in the VIX index is 1.81 percentage points higher than its next-highest record (80.86) on November 20, 2008 (John and Li, 2021). Importantly, the VIX index showed high volatility with a standard deviation of 11.03 (Table 1). Overall, it can be observed that the COVID-19 pandemic generated fear in the market participants and led to high volatility in the US stock market.

Table 1

Descriptive statistics

	MEAN	SD	MIN	MAX	SKEW	KURT
VIX futures	30.53	11.23	19.97	82.69	2.28	5.64
VIX index	29.75	11.03	18.86	82.69	2.36	6.20
Volume	124,610.8	83,549.2	902	436,781	1.796	3.415
Transaction costs	29.77	17.92	1.97	79.94	0.638	-0.427
Market conditions (S&P500)	2,995.63	311.49	2,237.4	3,716.48	-0.345	-0.985
World COVID-19 (cases)	24,626,613	20,776,137	90,923	73,672,840	0.661	-0.636
World COVID-19 (deaths)	767,528	479,491	3,121	1,695,407	0.037	-1.051
US COVID-19 (cases)	5,481,335	4,305,436	100	16,845,137	0.691	0.233
US COVID-19 (deaths)	154,067	83,392	6	308,101	0.359	-0.745

Notes: No of Observations =360, SD = standard deviation, SKEW = Skewness, KURT = Kurtosis

Figure 1: *Daily VIX index, March 3, 2020 to Feb 26, 2021*

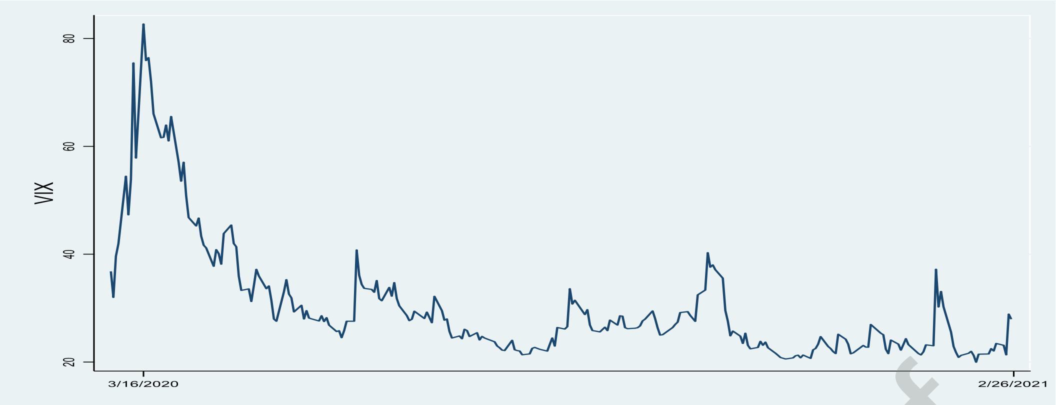


Figure 2: *COVID -1 9 pandemic cases and deaths (in logarithm), March 3, 2020 to Feb 26, 2021*

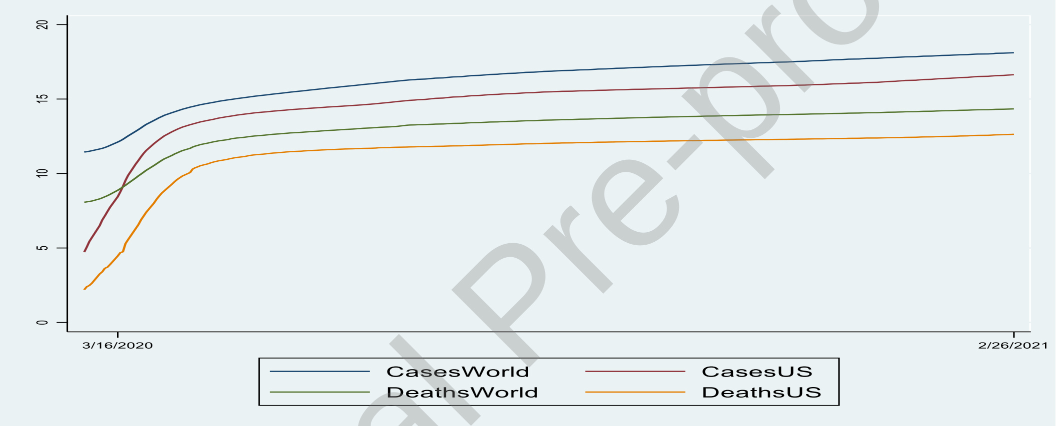
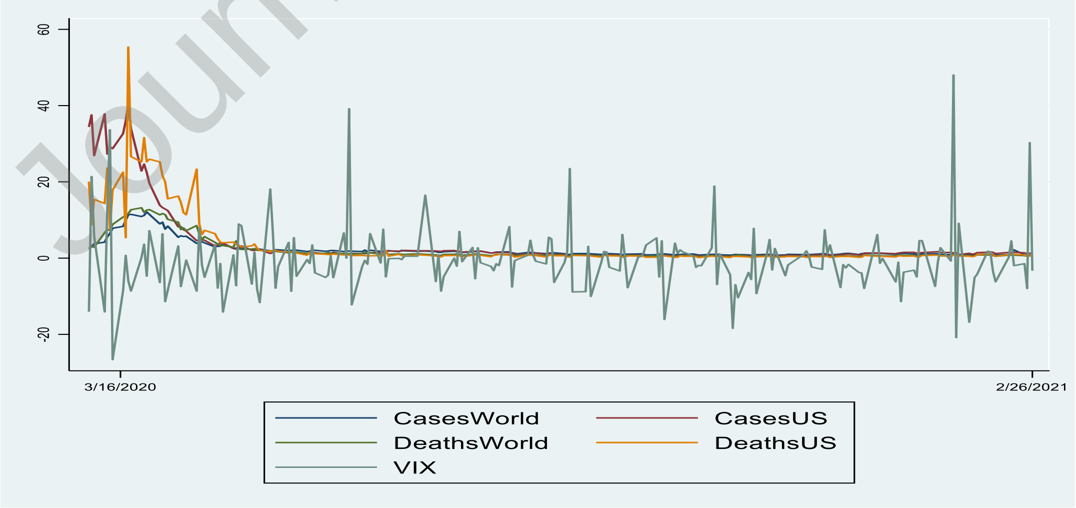


Figure 3: *COVID-19 pandemic and VIX spot index (growth rates), March 3, 2020 to Feb 26, 2021*



Before testing for the determinants of implied volatility in the US stock market, it is necessary to test for the stationarity of all variables being studied. We start our empirical analysis by presenting the unit root test through the General Least Squares

Augmented Dickey-Fuller (GLS-ADF) test, as recommended by Elliott et al. (1996). The results in Table 2 provide strong evidence that all variables (except the VIX index) are stationary in their first differences. The VIX index turns out to be stationary at its levels.

Table 2

Unit root tests

	Levels	**First differences**
VIX futures	-1.35(3)	-6.48(2)***
Volume	-1.34(4)	-6.84(3)***
Transaction costs	-1.39(3)	-6.55(2)***
Market conditions (S&P500)	-1.44(3)	-6.60(2)***
VIX index	-6.85(2)***	
World COVID-19 (cases)	-1.27(3)	-6.96(2)***
World COVID-19 (deaths)	-1.25(3)	-6.86(2)***
US COVID-19 (cases)	-1.23(4)	-6.72(3)***
US COVID-19 (deaths)	-1.26(3)	-6.71(2)***

The numbers in parentheses denote the lag length used to obtain white noise residuals. The lag length was selected using the Akaike Information Criterion. ***: $p \leq 0.01$.

This study focuses on the relationship between VIX and the COVID-19 pandemic, conditional on the different VIX circumstances and the cases of COVID-19. Specifically, the analysis considers that quantiles reflect low or high volatility of the VIX index and whether the COVID-19 cases or deaths are low or high. To investigate the dynamic dependencies between VIX and changes in COVID-19 cases or deaths during the different states, the linkages between the 10th and 50th quantiles are considered (the results from the 50th quantile to the 90th quantile were substantially similar). We define that the dependencies during the "normal" state are determined through the centrally located quantile, i.e., the 50th quantile, while the quantile regressions will be implemented for lower quantiles (10^{th}). The findings will help us to determine how changes in COVID-19 impact VIX at the low tails of their return distributions and indicate the difference in the effect of COVID-19 changes on VIX across different conditions. For technical (algorithmic) reasons, the remaining control variables cannot be decomposed in quantiles, but their mean effect is considered throughout the estimates.

Based on the QQR approach expressed in Equation (4), the entire dependence between the quantile of VIX and the quantile of COVID-19 measures can be synthesized by two main parameters: $\beta_0(\theta,\tau)$ and $\beta_1(\theta,\tau)$. These are the intercept term and the slope coefficient, respectively. Both parameters vary depending on the different VIX states and the cases of COVID-19. The empirical findings based on quantile regression estimates are reported in Table 3a. For comparison purposes only, Table 3a also reports the estimates based on the mean distribution. The empirical results highlight that the parameter estimates vary across the OLS and quantiles, with the findings being consistent across both World and US COVID-19 definitions. The quantile findings are in contrast to those offered by OLS regression coefficients. The results in Panel A and B correspond to COVID-19 total cases (both World and US), while those in Panel C and D correspond to COVID-19 total deaths (both World and US).

In terms of the constant term, we can observe that the intercept term in the mean distribution estimates is generally statistically significant, while quantile estimates are greater at the bottom quantiles when both the COVID-19 pandemic and VIX are low. Next, in terms of the direct relationship between the VIX index and COVID-19 changes, the findings illustrate that the mean distribution estimates are positive and statistically significant at 10%. When we focus on the quantile estimates at low levels of VIX and low changes in COVID-19, the relationship is statistically insignificant. This relationship gets stronger and statistically significant at 1% and at higher quantiles. The results remain consistent across both World and US definitions of the COVID-19 event, although they get stronger when the pandemic is expressed using the total death definition (from 1.879 to 2.203), clearly indicating that higher death rates (comparatively to pandemic cases) tend to stronger increase the fear across financial markets. Overall, when the death rates were intensified, markets experienced increased fear thus motivating policymakers to step in to mitigate the negative impact of the crisis on global markets and economies.

Considering the COVID-19 period under study and our econometric approach, this work is comparable with only two studies. The emerging literature on the impact of the COVID-19 pandemic on implied volatility has so far produced mixed results. For example, Just and Echaust (2020) in their cross countries study argue that the COVID-19 pandemic (case/deaths) has no impact on implied volatility in the US. Their empirical results across a sample of 12 countries show that the COVID-19 pandemic has a positive impact on implied volatility only in Italy. In contrast, our findings document a clear positive impact of the COVID-19 pandemic on implied volatility in the US. Our findings confirm and extend the conclusion of Albulescu (2021) who finds that the COVID-19 pandemic has a positive impact on VIX. While our study covers an extended COVID-19 period, Albulescu (2021) analyzed the data between March 11, 2020 and May 15, 2020. Interestingly, the rapidly growing literature on the financial markets has indicated record levels of economic uncertainty and volatility in response to the COVID-19 contagion effects (Altig et al., 2020), leading to fear among investors and thus turbulence in the global financial markets (John and Li, 2021).

Across all cases, VIX displays strong persistence since the lagged value estimate is relatively high. The remaining control variables exert a similar impact on VIX volatility across all quantiles under consideration, as well as across both definitions of COVID-19. These estimates are in line with those indicated in the relevant literature on VIX determinants. For instance, the results related to the trading volume indicate a positive association with VIX volatility and a positive link between transaction costs with VIX volatility, with both receiving support from studies such as those by Chen and Gau (2010), Fricke and Menkhoff (2011), and Chang, Chen, Chou, and Gau, (2013). The estimates concerning market conditions are consistent with Shu and Zhang (2012), showing a negative relationship with VIX volatility. Finally, the relationship between the VIX index and VIX futures is positive, which receives statistical support from the literature (Yoon et al., 2022).

Table 3a

OLS and quantile results: The dependent variable is VIX

	Panel A: World COVID-19 (total cases)			**Panel B: US COVID-19 (total cases)**		
	OLS	**10^{th}**	**50^{th}**	**OLS**	**10^{th}**	**50^{th}**
β_0	-1.136**	-1.668***	-0.657	-1.176**	-1.678***	-0.684
	[0.03]	[0.00]	[0.16]	[0.02]	[0.00]	[0.13]
VIX index (-1)	0.439***	0.496***	0.517***	0.442***	0.489***	0.568***
	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]
β_1	0.779*	0.249	1.869***	0.792*	0.262	1.879***
	[0.08]	[0.19]	[0.00]	[0.06]	[0.15]	[0.00]
ΔVIX futures	1.447***	1.753***	2.542***	1.438***	1.789***	2.734***
	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]
ΔVolume	0.077***	0.068***	0.086***	0.084***	0.077***	0.082***
	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]
ΔTransaction costs	-0.160***	0.159***	0.188***	-0.159***	0.150***	0.179***
	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]
ΔMarket conditions	-0.063**	-0.053**	-0.070**	-0.056**	-0.049**	-0.068**
	[0.02]	[0.03]	[0.02]	[0.02]	[0.03]	[0.02]
Pseudo R^2	0.62	0.61	0.81	0.63	0.62	0.78
	Panel C: World COVID-19 (total deaths)			**Panel D: US COVID-19 (total deaths)**		
β_0	-1.456***	-1.563***	-0.593	-1.472***	-1.588***	-0.602
	[0.00]	[0.00]	[0.14]	[0.00]	[0.00]	[0.13]

VIX index (-1)	0.491***	0.526***	0.585***	0.503***	0.563***	0.611***
	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]
β_1	0.735*	0.282	2.095***	0.749*	0.254	2.203***
	[0.08]	[0.16]	[0.00]	[0.07]	[0.18]	[0.00]
ΔVIX futures	1.843***	1.818***	2.769***	1.849***	1.828***	2.894***
	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]
ΔVolume	0.083***	0.071***	0.096***	0.088***	0.076***	0.099***
	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]
ΔTransaction costs	-0.174***	0.159***	0.198***	-0.178***	0.171***	0.202***
	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]
ΔMarket conditions	-0.057**	-0.049**	-0.084**	-0.058**	-0.050**	-0.090***
	[0.03]	[0.03]	[0.02]	[0.03]	[0.03]	[0.01]
Pseudo R^2	0.64	0.65	0.85	0.66	0.68	0.84

Figures in brackets denote p-values. ***: p≤0.01; **: p≤0.05; *: p≤0.10.

Given a concern that VIX variable is not used on the difference mode, this part of the empirical analysis repeats the above analysis, but this time the VIX variable is expressed in the first differences. and the results are reported in Table 3b. As Table 3b shows, the results indicate a very strong similarity to those presented in Table 3a[7].

Table 3b

OLS and quantile results: The dependent variable is ΔVIX

	Panel A: World COVID-19 (total cases)			**Panel B: US COVID-19 (total cases)**		
	OLS	**10th**	**50th**	**OLS**	**10th**	**50th**
β_0	-1.054**	-1.594***	-0.617	-1.089**	-1.569***	-0.622
	[0.04]	[0.00]	[0.18]	[0.03]	[0.00]	[0.14]
ΔVIX index (-1)	0.557***	0.592***	0.584***	0.511***	0.549***	0.612***
	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]
β_1	0.736*	0.226	1.955***	0.764*	0.233	2.246***
	[0.09]	[0.21]	[0.00]	[0.07]	[0.16]	[0.00]
ΔVIX futures	1.463***	1.789***	2.565***	1.445***	1.799***	2.833***
	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]
ΔVolume	0.072***	0.060***	0.094***	0.077***	0.072***	0.102***
	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]
ΔTransaction costs	-0.154***	0.145***	0.197***	-0.147***	0.144***	0.194***
	[0.00]	[0.01]	[0.00]	[0.00]	[0.01]	[0.00]
ΔMarket conditions	-0.057**	-0.048**	-0.079**	-0.050**	-0.043**	-0.077**
	[0.03]	[0.04]	[0.02]	[0.03]	[0.04]	[0.02]

[7] We are very grateful to an anonymous reviewer who recommended this approach.

Pseudo R^2	0.60	0.58	0.84	0.61	0.59	0.80
	Panel C: World COVID-19 (total deaths)			**Panel D: US COVID-19 (total deaths)**		
β_0	-1.409***	-1.511***	-0.564	-1.453***	-1.541***	-0.569
	[0.00]	[0.00]	[0.16]	[0.00]	[0.00]	[0.15]
ΔVIX index (-1)	0.519***	0.544***	0.599***	0.512***	0.570***	0.643***
	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]
β_1	0.702*	0.266	2.253***	0.715*	0.224	2.296***
	[0.09]	[0.19]	[0.00]	[0.08]	[0.20]	[0.00]
ΔVIX futures	1.835***	1.802***	2.794***	1.815***	1.801***	2.927***
	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]
ΔVolume	0.077***	0.064***	0.113***	0.081***	0.062***	0.135***
	[0.00]	[0.01]	[0.00]	[0.00]	[0.01]	[0.00]
ΔTransaction costs	-0.168***	0.152***	0.206***	-0.159***	0.164***	0.224***
	[0.00]	[0.01]	[0.00]	[0.00]	[0.00]	[0.00]
ΔMarket conditions	-0.052**	-0.045**	-0.091**	-0.052**	-0.042**	-0.097***
	[0.04]	[0.04]	[0.02]	[0.04]	[0.04]	[0.01]
Pseudo R^2	0.62	0.64	0.87	0.63	0.66	0.87

Figures in brackets denote p-values. ***: $p \leq 0.01$; **: $p \leq 0.05$; *: $p \leq 0.10$.

In the next part of the empirical analysis, we turn our attention to predicting the QQR model both with and without the COVID-19 measures. The goal of this part of the empirical analysis is to establish whether including COVID-19 measures yields better forecasts. The analysis employs a rolling window of 50 observations to estimate both the mean distribution regression and quantile coefficients regression to assess their out-of-sample performance in the remainder of the sample by looking at l- and 5-day ahead forecasts. The benchmark modeling period for the forecast is from March 2020 through November 2020, while the out-of-sample forecasting period runs from December 2020 through March 2021. Table 4 displays the descriptive results of the out-of-sample evaluation. In particular, the table reports the Mean Absolute Forecast Error (MAE) and the Mean Squared Forecast Error (MSE). The MAE and MSE criteria tell virtually the same story. The model that includes the COVID-19 variable produces better 1- and 5-day forecast results, and the results remain consistent in terms of both the World and US COVID-19 cases.

Table 4

Forecasting performance

	Panel A: World COVID-19 (cases)			
	Without COVID-19		**With COVID-19**	
Forecasting horizon	MAE	MSE	MAE	MSE
1-day	0.0553	0.0038	0.0371	0.0028
5-day	0.0573	0.0050	0.0426	0.0041

	Panel B: World COVID-19 (deaths)			
	Without COVID-19		**With COVID-19**	
Forecasting horizon	MAE	MSE	MAE	MSE
1-day	0.0549	0.0039	0.0244	0.0020
5-day	0.0574	0.0049	0.0356	0.0032

	Panel C: US COVID-19 (cases)			
	Without COVID-19		**With COVID-19**	
Forecasting horizon	MAE	MSE	MAE	MSE
1-day	0.0535	0.0033	0.0360	0.0023
5-day	0.0562	0.0050	0.0414	0.0038

	Panel D: US-COVID-19 (deaths)			
	Without COVID-19		**With COVID-19**	
Forecasting horizon	MAE	MSE	MAE	MSE
1-day	0.0538	0.0031	0.0217	0.0017
5-day	0.0559	0.0043	0.0330	0.0031

Forecasting performance is gauged through the mean absolute forecast error (MAE) and the mean squared forecast error (MSE).

Moreover, we complement the above forecasting analysis by running the unconditional Giacomini-White test for the mean absolute forecast error (Giacomini and White, 2006). Table 5 reports the p-values for testing the null hypothesis that the two models perform equally well in terms of mean absolute forecast error. The findings highlight that the p-values signify the rejection of the null hypothesis, implying that the model with the COVID-19 variable(s) included performs significantly better than the model without it under both COVID-19 definitions and at both the 1- and 5-day horizons at the 1% level.

Table 5

Giacomini-White tests for the mean absolute forecast error

	Panel A. World COVID-19 (cases)	**Panel B. US COVID-19 (cases)**
	Without & With COVID-19	Without & With COVID-19
1-day	0.02	0.01
5-day	0.02	0.01
	Panel C. World COVID-19 (deaths)	**Panel D. US COVID-19 (deaths)**
Forecasting horizon	Without & With COVID-19	Without & With COVID-19
1-day	0.01	0
5-day	0.01	0

The p-values in each entry correspond to the modified Giacomini-White test for the null hypothesis that the two models perform equally well in terms of mean absolute forecast error.

4. Conclusion

The outbreak of the COVID -19 disease has presented an unprecedentedly fearsome challenge for households, governments, and market participants across the world. In this study, we examined how the implied volatility dynamics, measured by the CBOE VIX index, were affected by the COVID-19 pandemic. Our novel empirical framework allows the dynamic connection between VIX and COVID-19 to be captured in different VIX conditions (i.e., low and high), and where the COVID-19 pandemic is measured either as cases or deaths (i.e., low and high). Using a daily data, the analysis examined the impact of the COVID-19 pandemic on the US stock market volatility over the period March 3, 2020 through February 26, 2021. The study provides evidence that high COVID-19 cases exert significant impact on the implied volatility under high uncertainty conditions. It also documents that low COVID-19 cases appear to have no impact on implied volatility in the US market, suggesting that financial markets respond only to extreme fear.

The results carry some significant implications. In particular, they could help market participants to understand the behavior of the markets across different types of crises and thus help participants to make rational decisions in terms of their trading strategies. Accordingly, investors and portfolio managers can use the results of this study to measure, monitor, and effectively manage portfolio risks. Furthermore, our study's findings could help them to better estimate the maximum value they might lose on their current investments and accordingly plan for the future. Our findings are relevant for regulators and policymakers, who should consider the presence of jump-tail risks, such as the COVID-19 pandemic, and any potential change to risk levels during times of stress when they are estimating, quantifying, or ranking financial systemic risks. Under the downside risk tendency, the connectedness measures are useful for the formulation of policies aimed at preserving financial stability. Importantly, dynamic policies are urgently needed to smooth systemic risks when these dramatically increase, as well as to foster the financial markets' resilience to distress, especially given the magnitude of the COVID-19 pandemic. Therefore, policymakers can make efforts to diversify market risks and, thus, maintain stability. Our results offer support for the US policy response by the Federal Reserve Board and the government, which aimed to limit the instability effect of the COVID-19 shock on financial markets. It is important to highlight that our empirical analysis ends in February 2021, a period where the global economy started experiencing the positive impact of the vaccination process. However, by that time the fear of deaths from the pandemic crisis was at high levels given the uncertainty regarding the vaccination outcome. Therefore, people generally felt that the market was dislocated, and policy countermeasures included certain anticipated actions and the use of existing tools, as well as new developments and new policy solutions. Although these policy measures could have the potential to stabilize the market to a certain extent, the uncertainty/fear surrounding deaths from the pandemic was highly threatening capital markets. Overall, the results of this study could be used as a pilot for the future where governments or any other policymakers need to prepare for similar health crises to mitigate any adverse effects on economic growth and stabilize global financial markets.

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Conflict of interest

We declare that we are the authors of this unpublished work and there is no conflict of interest.

Highlights

- We propose a novel empirical approach to analyze the dynamic relationship between COVID-19 pandemic categories (i.e., low and high) and implied volatility conditions (i.e., low and high).
- Our empirical approach allows us to study how market participants perceive jump-tail risks and react to the COVID-19 pandemic.
- We document that increased death rates tend to increase fear across financial markets.
- Our results highlight that high COVID-19 cases have a significant positive impact on implied volatility under high uncertainty conditions.