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Risk Modeling and Connectedness Across Global and Industrial US Fintech Stock Market: Evidence from the COVID-19 Crisis

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ABSTRACT

The main **purpose** of this paper is to test the performance of GARCH models in estimating and forecasting VaR (value at risk) of the US Fintech stock market from July 20, 2016, to December 31, 2021. In addition, this study examines the impact of COVID-19 on the risk spillover between the adequate VaR series of the US global KFTX index and the five Fintech industries. Specifically, we compare different VaR estimates (862 in-sample daily returns) and predictions (550 out-of-sample daily returns) of several GARCH model specifications under a normal and Student-t distribution with 1% and 5% significance. The Backtesting results indicate that I-GARCH with Student-t distribution is a good model for estimating and forecasting VaR of the US Fintech stock market before and during COVID-19. Moreover, the total connectedness results suggest that global and each Fintech industry increases significantly under turbulent market conditions. Given these considerations, this paper provides policymakers and regulators with a better understanding of risk in the Fintech industry without inhibiting innovation.

Keywords: value at risk; fintech stock market; GARCH model specifications; COVID-19; VaR series; connectedness

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INTRODUCTION

The financial technology (Fintech) industry invests in innovations by allowing firms to offer new products, new business processes, and new business models in order to support evolving investor preferences. The wide application of technological networks has developed an original financial model that has greatly affected both economic and financial dimensions [1, 2]. Even though these new technologies are changing the world of the US financial industry by creating huge rewards, they also give rise to huge risks [3].

Since the global financial crisis in 2008, markets have experienced a series of turbulences, namely, the outbreak of the coronavirus's (COVID-19) health crisis that gave rise to various shock waves affecting financial stock markets [4–6]. In this vein, the existence of several confirmed cases of the COVID-19 pandemic in the USA* helped the rise of digital adoption due to social distancing. In fact, this rapid development, along with the rise of uncertainties and volatility, might be the reason behind the increase in the risk of the Fintech stock market. For this reason, it is important to evaluate the risk of the US stock market based on the technological area before and during the COVID-19 pandemic.

The COVID-19 outbreak aggravated risk in stock markets, which made investors more prudent regarding the risk measurement of the Fintech industry. This research aims to investigate the best accurate VaR models and to study the impact of COVID-19 on the dependence among value at risk of the global US Fintech stock market and each Fintech industry. Using three important measures of Value at Risk models: integrated GARCH (1, 1); standard GARCH (1, 1), and component standard GARCH (1, 1) based on normal and student-t distributions with 1% and 5% significance levels, we apply two steps of VaR backtesting test: Kupiec's unconditional and Christoffersen's conditional coverage procedures. Following this, we examine the volatility spillover effects among the predictive abilities of the selected VaR models by using the index of [7].

Therefore, the present study provides three major contributions to the risk of the Fintech industry. Firstly, this paper investigates the Value at Risk of the Fintech stock market in order to understand the market's risk management, especially, during the COVID-19 pandemic. Secondly, it provides evidence that widely used methods give reliable VaR estimates and forecasts for calm periods (before COVID-19) and turmoil periods (during COVID-19), respectively. Thirdly, the risk spillovers analysis between the global US Fintech index and each Fintech industry allows a deep explanation of whether there is a change in the strength of system spillovers between pairwise VaR series from pre- and mid-COVID-19.

To the best of our knowledge, no previous study was made to investigate the performance of the accurate VaR model for estimating and forecasting the risk of the US Fintech index and each Fintech industry before and during COVID-19. Moreover, the connectedness analysis between different risks helps policies preserve financial stability, investment and hedging strategies for the benefit of investors, portfolio managers and risk managers.

Our purpose can be pressing for portfolio risk managers, policymakers, and regulators because of its central impact on managing risk in the context of financial instability. The remainder of this study is organized as follows: Section 2 provides a literature review. Section 3 states the methodology. Section 4 presents data and descriptive statistics. Section 5 consists of empirical findings. The final part is a conclusion to our study.

LITERATURE REVIEW

A growing number of research studies are dealing with the estimation and forecasting of stock market risk by using different VaR models.

For instance, Assaf [8] analyzed the out-of-sample performance of VaR models based on four MENA equity markets using the APARCH model. The study shows that the APARCH model with student distribution is the optimal model for the estimation of VaR compared to those with a normal distribution. Tabasi et al. [9] implemented GARCH models in order to model the volatility-clustering feature. They concluded that the use of the t-student distribution function was better than using the Normal one in that it updated the model VaR parameter estimation.

Recently, Emenogu et al. [10] stated that while GARCH models are robustly persistent, only IGARCH and EGARCH models are unstable. In addition, S-GARCH and GJR-GARCH models underestimated VaR with student-t innovation. Ben Ayed et al. [11] explored the performance of Value at Risk models for North Africa and Middle East Islamic indices by using risk metrics and other GARCH models. They suggested using risk metrics in calm periods and both GARCH and APARCH in turbulence periods. Amiri et al. [12] used GARCH models to estimate VaR with various return distributions of different industries in the Tehran Stock Exchange and they found that the GJR-GARCH model with NIG distribution is the best accurate model. Haddad et al. [13] investigated the predictive performance of the Value at Risk model by using several GARCH specifications in order to estimate and forecast the Value at Risk of six major cryptocurrencies. Among principal results, they found that the I-GARCH model outperforms other models in both the in-sample and out-sample frameworks. Shaik and Padmakumari [14] used various VaR models in order to predict their performance based on the backtesting test in the case of the BRICS and US stock market indices from 2006 to 2021. The results exhibited that EWMA performs better VaR estimation than N and HS estimation models for all indices. Moreover, a limitation of the accurate predictive VaR models occurred during the COVID-19 period. Mrkvička et al. [15] analyzed the accuracy of five VaR methods for small and medium-sized enterprises to estimate future exchange rate losses during one year. Backtesting results revealed that parametric-VaR is the most accurate for estimating future losses in a given period.

METHODOLOGY

GARCH Model Specifications

In this paper, we employ robust GARCH models to estimate and forecast the Value at Risk in financial markets. In this section, different GARCH models are described.

Standard GARCH Model (sGARCH)

The standard GARCH model proposed by Bollerslev [16] is expressed as follows:

$$\sigma_t^2 = \left(w + \sum_{j=1}^{m} \zeta_j v_{jt} \right) + \sum_{j=1}^{q} \alpha_j \varepsilon_{t-j}^2 + \sum_{j=1}^{p} \beta_j \sigma_{t-j}^2 \quad (1)$$

σ_t^2 denotes the conditional variance, where $\boldsymbol{w}$ is the constant term and $\boldsymbol{v}_{jt}$ denotes exogenous variables and

* World Health Organization. Novel Coronavirus (2019-n CoV): situation report, 19. World Health Organization. 2020. URL: https://apps.who.int/iris/handle/10665/330988 (accessed on 05.06.2023).

ε_t^2 are the residuals from the mean filtration process discussed previously.

Integrated GARCH model (iGARCH)

The integrated GARCH model proposed by Engle and Bollersev [17] can be briefly expressed as follows:

$$I_t = \varphi_t \varepsilon_t \text{ With } \varphi_t^2 = \alpha_0 + \beta_1 \varphi_{t-1}^2 + \left(1-\beta_1\right) I_{t-1}^2, \quad (2)$$

where $0 < \beta_1 < 1$; $\alpha + \beta = 1$.

This model is specified by the occurrence of unit-root in the variance and the persistence of the effect of squared shocks.

The Component Standard GARCH (Csgarch)

The component standard GARCH model of Lee and Engle [18] decomposes the component of the conditional variance into a permanent and transitory component to investigate the long- and short-term movements of volatility. The component model can be written as:

$$\sigma_t^2 = q_t + \sum_{j=1}^{q} \alpha_j \left(\varepsilon_{t-j}^2 - q_{t-j}\right) + \sum_{j=1}^{p} \beta_j \left(\sigma_{t-j}^2 - q_{t-j}\right), \quad (3)$$

where the permanent component of the conditional variance q_t is calculated as follows:

$$q_t = w + \rho q_{t-1} + \varphi\left(\varepsilon_{t-1}^2 - \sigma_{t-1}^2\right). \quad (3.1)$$

Where, the intercept of the GARCH model is time-varying following first-order autoregressive type dynamics.

Backtesting Test: Model Evaluation and Statistical Accuracy of VaR

A backtesting test is the process of comparing losses predicted by the value at risk (VaR) model to those experienced over the sample-testing period. Thus, there are two main tests generally used by researchers to select the most suitable VaR model.

The Kupiec Test

P. Kupiec's [19] test (UC test) is based on the proportion of Failures (POF) test, which examines whether the observed frequency of exceptions is statistically equal to the expected frequency of exceptions implied by the VaR confidence level. The likelihood ratio is given by:

$$LR_{POFF} = -2\log\left(\frac{(1-p)^{N-x} p^x}{\left(1-\frac{x}{N}\right)^{N-x}\left(\frac{x}{N}\right)^x}\right) \sim \chi_1^2, \quad (4)$$

$$P\_value = 1 - F\chi_1^2\left(LR_{POFF}\right), \quad (4.1)$$

where x is the number of failures, N is the number of observations. $F\chi_1^2\left(LR_{POFF}\right)$ is the cumulative distribution of χ_1^2.

The Christoffersen Test

Christoffersen [20] test (CCI) is based on the test of independence that measures whether the probability of observing an exception on a given day depends on the occurrence of an exception. The likelihood ratio is given by:

$$LR_{CCI} = -2\log\left(\frac{(1-\pi)^{n00+n10}\,\pi^{n01+n11}}{\left(1-\pi_0\right)^{n00}\pi_0^{n01}\left(1-\pi_1\right)^{n10}\pi_1^{n11}}\right) \sim \chi_1^2. \quad (5)$$

Diabold and Yilmaz Index

In order to capture the volatility dynamic connectedness between different VaR series, we used the spillover connectedness index method proposed by Diebold and Yilmaz [7]. This method is based on the decomposition of the forecast-error variance of a variable under a generalized vector autoregressive (VAR) model introduced by [21] and [22]. Taking into consideration the covariance of the stationary VAR with order (p) and M-dimensional vector, the endogenous variables Y_t of is defined as follows

$$Y_t = \varphi_1 Y_{t-1} + \varphi_2 Y_{t-2} + \varphi_3 Y_{t-3} + \ldots\ldots\ldots + \varphi_p Y_{t-p} + \varepsilon_t, \quad (6)$$

where $\varphi_1, \varphi_2, \varphi_3, \ldots, \varphi_p$ is a vector of M × M autoregressive coefficient matrix, and ε_t is the M-dimensional vector matrix of error terms that are independently and identically distributed. Thus, by reason of covariance stability, we can present the Moving Average of (1) as follows:

$$Y_t = \sum_{i=0}^{\infty} C_i \varepsilon_{t-i}, \quad (7)$$

where C_i is a vector of $M \times M$ coefficient matrices calculated by the below formula:

$$C_i = \Sigma \varphi_p C_{i-k}, \quad (7.1)$$

where $k = 1, \ldots, p$.

The H-step generalized for forecasting the error variance decomposition from variable i to variable k is expressed as follows:

$$\theta_{ik}(H) = \frac{\sigma_{kk}^{-1} \sum_{h=0}^{H-1} \left(e_i^{'} C_h \Sigma e_k\right)^2}{\sum_{h=0}^{H-1} (e_i^{'} C_h \Sigma C_h^{'} e_i)}, \quad (8)$$

for $i, k = 1, 2 \ldots, M$,

where σ_{kk}^{-1} is the k^{th} element diagonal of the error term, e_i is an $M \times 1$ selection vector with 1 as the i^{th} element and 0 otherwise, and H represents the forecasted horizon.

Based on the $M \times M$ matrix of variance decomposition (spillover index) $\theta_{ik}(H)$, which indicates the volatility shock effect of variable k on the forecast error variance of variable i, we have $\sum_{i=k}^{N} \theta_{ik}(H) \neq 1$. Thus, $\theta_{ik}(H)$ can be normalized as:

$$\bar{\theta}_{ik}(H) = \frac{\theta_{ik}(H)}{\sum_{k=1}^{M} \theta_{ik}(H)}, \quad (9)$$

where $\sum_{k=1}^{M} \bar{\theta}_{ik}(H) = N$ and $\sum_{i=1}^{M} \bar{\theta}_{ik}(H) = 1$.

According to this basic foundation of Diebold and Yilmaz [7], the total spillover connectedness index is given as:

$$TSCI(H) = \frac{\sum_{i,k=1,\, k \neq i}^{M} \bar{\theta}_{ik}(H)}{\sum_{k=1}^{M} \bar{\theta}_{ik}(H)} \times 100 =$$

$$= \frac{\sum_{i,k=1, i \neq k}^{M} \bar{\theta}_{ik}(H)}{N} \times 100. \quad (10)$$

DATA AND DESCRIPTIVE STATISTICS

In this paper, we use daily returns from the KFTX (KBW Financial Technology) Index in the US, which contains 48 companies classified into five industry sectors: Capital Markets, Financial Services, Computer Services, Professional Services, and Software. We obtained the data from the investing.com website. The full sample is divided into a sample size T that contains observations for the period July 20, 2016, to December 31, 2019, and a sample size H that contains observations for the period January 2, 2020, to December 31, 2021. For the KFTX index and all five industries, we compute daily logarithmic returns as follows:

$$r_t = 100 * \left(\log P_t - \log P_{t-1}\right).$$

Figure 1 depicts the daily returns of the US Fintech stock index and the US Fintech industries from 20.07.2016 to 31.12.2021. Since the outbreak of COVID-19, we can detect a sudden change in early 2020, compared to the rest of the period. *Table 1* presents the daily descriptive statistics of the return series. It shows that the average daily returns record a positive mean close to zero. In addition, all return series are negatively skewed and all Kurtosis values were greater than 3, implying that the distribution has heavier tails than the normal distribution. The Jarque-Bera statistics accepted the non-normality of all returns. In addition, the Ljung-Box Q-statistics on the square returns with 5 and 10 lags indicated significant serial autocorrelation. Engle's [23] ARCH Lagrange Multiplier (ARCH-LM) test with 2 and 5 lags and Ljung and Box's [24] Q-statistics assert the existence of an ARCH effect (volatility clustering). Then, the ADF unit root tests (Dickey and Fuller [25]) affirm the stationarity of all return series.

Figure 2 shows the QQ plots based on the empirical distribution for the normal and Student's t distributions. As illustrated, all return series are linear only in the student-T distribution, proving that the returns of the Fintech stock market and each Fintech industry have adopted a non-normal distribution and tapered fat tails.

EMPIRICAL RESULTS

Table 2 and *Table 3* shows the results of the in-sample (out-of-sample) backtesting test to estimate (predict) VaR before COVID-19 (during COVID-19) for the KFTX index and each Fintech industry.

VaR Backtesting Test before COVID-19

The first part of *Table 2* shows that the results of the expected and actual VaR exceeded the 1% and 5% significance levels and it is clear that all of the "Actual

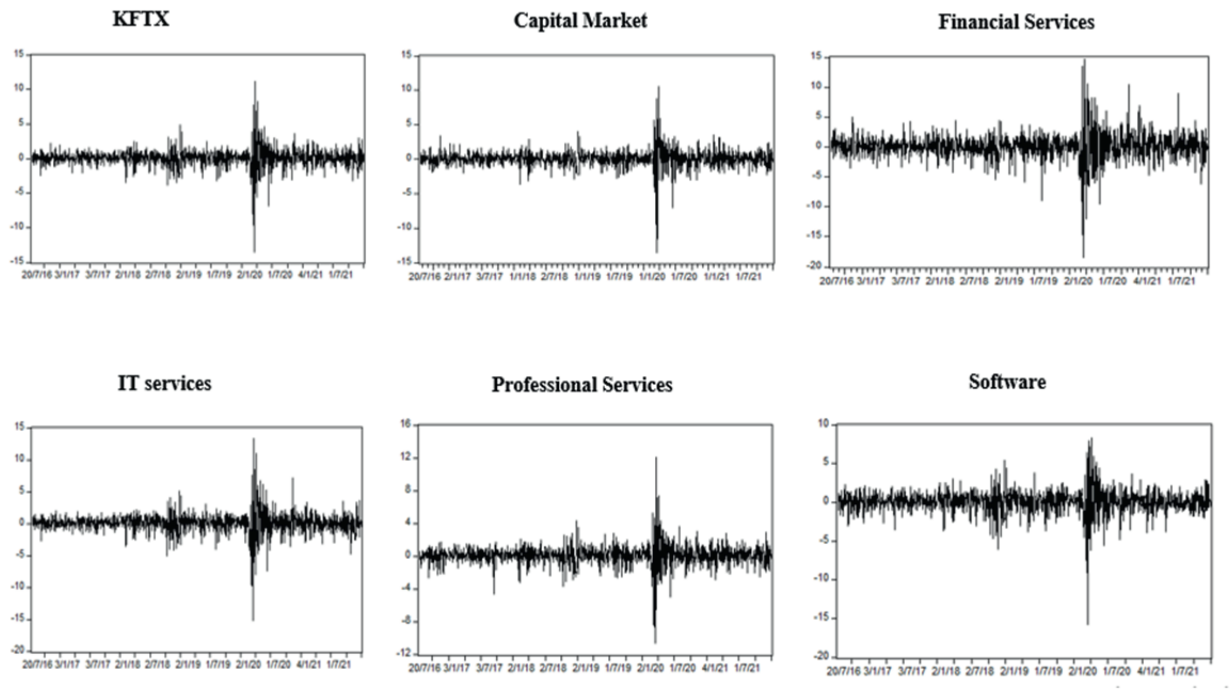

Fig. 1. **Stock Return of KFTX Index and Fintech Industries from July 2016 to December 2021 Period**

Source: Compiled by the authors.

VaR exceeded" values are greater than the "Expected VaR exceeded". This finding reveals that each GARCH model in this study underestimates the Va R.

Following *Table 2,* the results of Kupiec's POFF test indicate that GARCH models based on a normal distribution with α = 5% are satisfactory for the KFTX index and most industries except Professional Services and Software. Similarly, the existence of high levels of p-values means that the GARCH models perform better than the others. Thus, we can prove that the S-GARCH (1, 1) and I-GARCH models can produce a correct number of exceedances at the 5% level in some cases, but this is still insufficient. Then, with α = 1%, the results show that the GARCH models based on the normal distribution provided poor performance among the value-at-risk estimations. Therefore, concerning the student-t distribution, we can notice that the S-GARCH and CS-GARCH models with α = 5% and α = 1% perform well in correcting the exceedances referring to the outcomes of the capital market and financial services industries. Notably, the performance of the I-GARCH model based on the student-t distribution was found to be exceptionally faithful to the models with α = 1%, such that the Kupiec's Poff test failed to reject the null hypothesis of correct overshoots with high p-values in most outcomes. Therefore, we can conclude that the I-GARCH model with student-t distributions produces the correct number of exceedances. Second, the Christoffersen test allows us to perceive whether the estimated GARCH models suffer from volatility clustering or not. Accordingly, the results prove that the S-GARCH model based on the student-t distribution with α = 5% and α = 1% is appropriate to capture volatility clustering in the KFTX index. Moreover, in most cases, GARCH models can quickly accept the combined assumption of correct overshoot coverage and overshoot independence, especially the I-GARCH model based on the student-t distribution with α = 1%. Therefore, the I-GARCH model can be considered an appropriate VaR model for estimation during the pre-COVID-19 period.

In light of these results, the backtesting test indicated that the GARCH model specifications with the student-t distribution generally yield more adequate measures compared to models based on the normal distribution. Furthermore, these results are endorsed by the qq plots in *Figure 2*, which indicate that the fintech stock market is not normally distributed.

VaR Backtesting Test during COVID-19

The objective of this step is to perform a comprehensive evaluation of the quality of VaR forecasts for the KFTX

Table 1

Descriptive Statistics

Fintech index and industries	Starting Date	Nb. Of obs	Mean	SD	Skewness	Kurtosis	J–B	K–S	ARCH(2)	ARCH(5)	Q(5)	Q(10)	ADF
KFTX	20.07.2016	1375	0	1.3533	−1.0023	18.6544	20137.619 [0.00]	0.0858 [0.00]	0.7623 [0.00]	0.59 [0.00]	86.0213 [0.00]	244.1484 [0 .00]	−11.6504 [0.00]
Capital Market	20.07.2016	1375	0.0629	1.2982	−1.0794	23.3299	31427.078 [0.00]	0.0769 [0.00]	0.606 [0.00]	0.5441 [0.00]	128.9838 [0.00]	321.2845 [0.00]	−10.0564 [0.00]
Financial services	20.07.2016	1375	0.0558	2.2031	−0.4696	11.3581	7436.202 [0.00]	0.121 [0.00]	1.8022 [0.00]	1.5515 [0.00]	31.6524 [0.00]	85.8605 [0.00]	−14.0381 [0.00]
IT services	20.07.2016	1375	0.0447	1.5799	−0.6795	16.9851	16621.992 [0.00]	0.062 [0.00]	0.8971 [0.00]	0.6028 [0.00]	59.2129 [0.00]	193.7611 [0.00]	−9.76498 [0.00]
Professional services	20.07.2016	1375	0.0754	1.2574	−0.4778	16.1129	14916.002 [0.00]	0.0863 [0.00]	0.5915 [0.00]	0.4587 [0.00]	35.5169 [0.00]	133.5615 [0.00]	−9.7947 [0.00]
Software	20.07.2016	1375	0.0689	1.5152	−1.1694	13.5427	10813.059 [0.00]	0.0668 [0.00]	1.0597 [0.00]	0.7646 [0.00]	56.66516 [0.00]	137.96249 [0.00]	−12.3851 [0.00]

Source: Compiled by the authors.

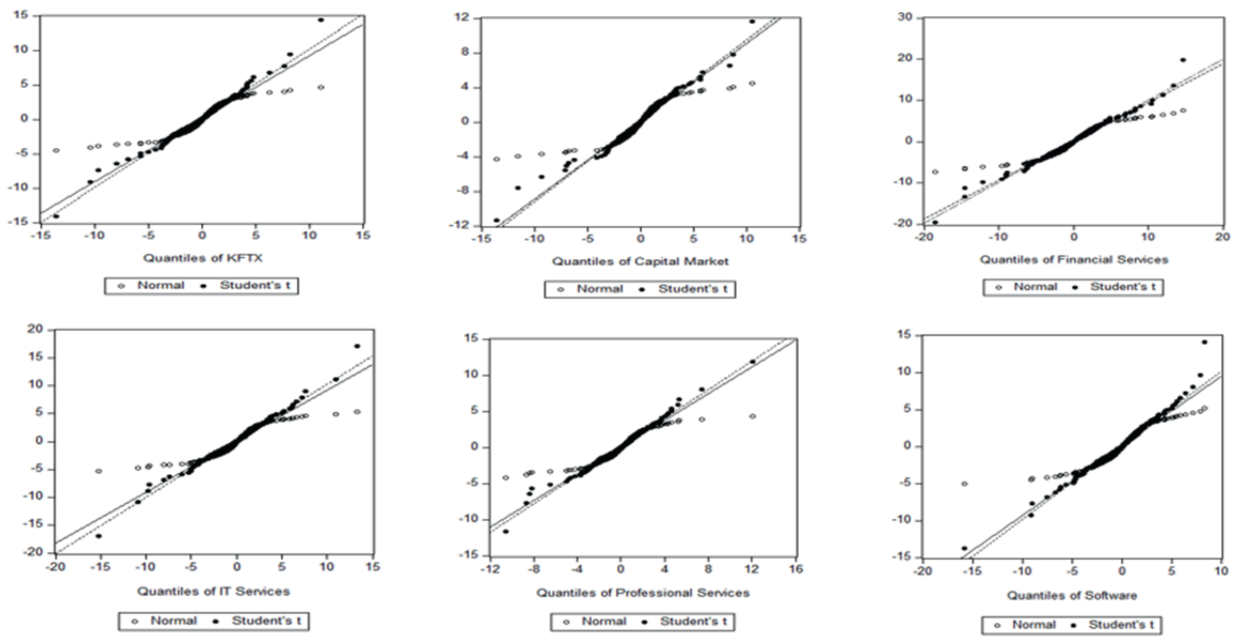

Fig. 2. **QQ Plots of KFTX Index and Fintech Industries for Both Normal and Student Distributions**

Source: Compiled by the authors.

index and Fintech industries during COVID-19: one day in advance by applying an iterative procedure from the estimation window to the end of the period. *Table 3* presents the results of Kupiec and Christoffersen's tests of the out-of-sample assessment during COVID-19 to capture the appropriate VaR forecasts at the 5% and 1% levels.

First, we show that the GARCH models in the out-of-sample procedure underestimate Va R. In general, results from *Table 3* indicate that the models with the student-t distribution give a better prediction of the one-ahead VaR than the models with the normal distribution for both 5% and 1%. In particular, the S-GARCH, I-GARCH, and CS-GARCH models based on the normal distribution with $\alpha = 5\%$ show poor forecasting performance for the trading position in the KFTX index and across all industries, except for the I-GARCH model, which performs consistently in the Capital Market, Financial Services, and Software industries. Subsequently, with an $\alpha = 1\%$, the results of the Kupiec test of all GARCH models based on the normal distribution give unsatisfactory results, referring to the rejection of the null hypothesis in the global Fintech stock market. Concerning student-t distribution, it appears that almost GARCH models with $\alpha = 5\%$ do not perform correctly due to their small p-values, especially in Capital Market, Professional Services and Software industries. Besides, we can infer that S-GARCH, I-GARCH and CS-GARCH models have an exceptional job of producing correct exceedances at the 1 percent level in the majority of returns. Especially, I-GARCH model offered the best performance in the KFTX index and five Fintech industries for predicting the one-day VaR forecast. Results from the Christofferson test were similar to those obtained from the Kupiec Poff test. Therefore, we can say that these models produce a correct coverage of exceedances and are independent of failures. With these results, we can confirm the importance of incorporating the I-GARCH model with the student-t distribution for VaR prediction of the Fintech industry in the US, due to its persistent variance. Thus, this property allows the existing evidence to have a significant effect on forecasting conditional variance.

Our results are consistent with those of Chu et al. [26], who selected twelve GARCH-type models in order to represent the volatility of seven major crypto-currencies. They concluded that I-GARCH and GJR-GARCH were the best-fitting volatility models in the case of the crypto-currency market. In addition, Naimy et al. [13] used six famous crypto-currencies, namely Bitcoin, Dash, Dogecoin, Litecoin, Monero, and Ripple. The results show that I-GARCH (1, 1) is the best model for Monero.

Volatility Spillover Effects

Table 4 presents the VaR-based descriptive statistics of the KFTX Index and each Fintech industry before and

Table 2

Summary of Backtesting Results of before COVID-19 Period

Backtesting tests	SGARCH-N		SGARCH-ST		IGARCH-N		IGARCH-ST		CS GARCH-N		CS GARCH-ST		SGARCH-N		SGARCH-ST		IGARCH-N		IGARCH-ST		CS GARCH-N		CS GARCH-ST	
	5%	1%	5%	1%	5%	1%	5%	1%	5%	1%	5%	1%	5%	1%	5%	1%	5%	1%	5%	1%	5%	1%	5%	1%
	KFTX												Financial services											
Expectedexceeded	46.2	9.2	46.2	9.2	46.2	9.2	46.2	9.2	46.2	9.2	46.2	9.2	46.2	9.2	46.2	9.2	46.2	9.2	46.2	9.2	46.2	9.2	46.2	9.2
ActualVaRexceeded	53	24	60	18	48	21	57	10	58	24	62	19	47	24	49	18	49	23	47	16	52	29	53	17
Actual%	5.7	2.6	6.5	2	5.2	2.3	6.2	1.1	6.3	2.6	6.7	2.1	5.1	2.6	5.3	2	5.3	2.5	5.1	1.7	5.6	3.1	5.7	1.8
LR. UC stat	1.02	16.57	4.01	6.589	0.08	11.1	2.61	5.29	2.97	16.569	5.19	8	0.016	16.57	0.182	6.889	0.182	14.7	0.016	4.114	0.751	27.29	1.02	5.292
(p-value)	−0.3	0	0	−0.01	−0.8	0	−0.1	−0.8	−0.1	0	0	−0.005	−0.9	0	−0.671	−0.01	−0.67	0	−0.9	−0.143	−0.39	0	−0.31	−0.02
Reject H0	NO	YES	YES	YES	NO	YES	NO	NO	NO	YES	YES	YES	NO	YES	NO	YES	NO	YES	NO	NO	NO	YES	NO	NO
LR. CCI stat	2.32	16.771(0)	4.24	7.432	1.28	11.6	3.32	6.23	3.55	16.771	5.57	8.665	0.204	16.77	0.266	7.306	0.977	14.9	1.108	4.68	0.757	27.31	1.02	5.89
(p-value)	−0.3		−0.1	−0.024	−0.5	0	−0.2	−0.4	−0.2	0	−0.1	−0.013	−0.9	0	−0.876	−0.03	−0.613	0	−0.58	−0.196	−0.69	0	−0.6	−0.05
Reject H0	NO	YES	NO	NO	NO	YES	NO	NO	NO	YES	NO	NO	NO	YES	NO	NO	NO	YES	NO	NO	NO	YES	NO	NO
	Capital Market												IT services											
Expectedexceeded	46.2	9.2	46.2	9.2	46.2	9.2	46.2	9.2	46.2	9.2	46.2	9.2	46.2	9.2	46.2	9.2	46.2	9.2	46.2	9.2	46.2	9.2	46.2	9.2
ActualVaRexceeded	54	25	54	13	45	24	44	10	54	15	59	13	58	23	64	21	55	21	58	11	59	24	75	20
Actual%	5.9	2.7	5.9	1.4	4.9	2.6	4.8	1.1	5.9	1.6	6.4	1.4	6.3	2.5	6.9	2.3	6	2.3	6.3	1.2	6.4	2.6	8.1	2.2
LR. UC stat	1.34	11.06	1.34	1.38	0.23	10.1	0.11	5.06	1.34	3.064	3.48	1.38	2.972	14.67	6.52	11.14	1.688	11.1	2.972	3.064	3.475	16.57	16.1	9.518
(p-value)	−0.2	0	−0.3	−0.24	−0.6	0	−0.7	−0.8	−0.2	−0.438	−0.1	−0.24	−0.85	0	−0.011	−0	−0.194	0	−0.06	−0.781	−0.06	0	0	−0
Reject H0	NO	YES	NO	NO	NO	YES	NO	NO	NO	NO	NO	NO	NO	YES	YES	YES	NO	YES	NO	NO	NO	YES	YES	YES
LR. CCI stat	1.57	11.41	1.57	7.851	0.71	9.41	0.49	8.72	2.38	8.406	4.77	9.274	3.49	14.94	8.002	11.59	1.716	11.6	4.452	4.453	3.891	16.77	16.3	10.09
(p-value)	−0.5	0	−0.5	−0.02	−0.7	0	−0.8	−0.5	−0.3	−0.015	−0.1	−0.197	−0.18	0	−0.01	−0	−0.424	0	−0.11	−0.408	−0.14	0	0	−0.01
Reject H0	NO	YES	NO	NO	NO	YES	NO	NO	NO	NO	NO	NO	NO	YES	YES	YES	NO	YES	NO	NO	NO	YES	YES	YES
	Professional services												Software											
Expectedexceeded	46.2	9.2	46.2	9.2	46.2	9.2	46.2	9.2	46.2	9.2	46.2	9.2	46.2	9.2	46.2	9.2	46.2	9.2	46.2	9.2	46.2	9.2	46.2	9.2
ActualVaRexceeded	62	28	68	20	63	28	64	16	63	30	75	21	63	24	64	18	55	25	65	16	57	24	66	20
Actual%	6.7	3	7.4	2.2	6.8	3	6.9	1.7	6.8	3.3	8.1	2.3	6.8	2.6	6.9	2	6	2.7	7	1.7	6.2	2.6	7.2	2.2
LR. UC stat	5.2	24.99	9.56	9.518	5.84	25	6.52	4.11	5.84	29.66	16.1	11.139	5.842 (0.016)	16.569 (0)	6.52 (0.011)	6.789 (0.01)	5.688 (0.011)	18.555 (0)	7.232 (0.007)	4.141	2.506	16.596 (0)	7.977(0.005)	9.518 (0.002)
(p-value)	0	0	0	−0.002	0	0	0	−0	0	0	0	−0.001								−0.043	−0.11			
Reject H0	YES	YES	YES	YES	YES	YES	YES	NO	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	NO	NO	YES	YES	YES
LR. CCI stat (p-value)	8.5	26.22	16.1	10.09	8.86	26.2	9.27	4.68	10.5	30.556	20	11.589	10.526 (0.005)	18.64 (0)	7.097(0.02)	9.306 (0.026)	7.426 (0.027)	20.387 (0)	13.043 (0.001)	5.3	4.181	16.771 (0)	10.223 (0.006)	10.405(0.006)
	0	0	0	−0.006	0	0	0	−0.1	0	0	0	−0.003								−0.071	−0.12			
Reject H0	YES	YES	YES	YES	YES	YES	YES	NO	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	NO	NO	YES	YES	YES

Source: Compiled by the authors.

Table 3

Summary of Backtesting Results of COVID-19 Period

Backtesting tests	SGARCH-N		SGARCH-ST		IGARCH-N		IGARCH-ST		CS GARCH-N		CS GARCH-ST		SGARCH-N		SGARCH-ST		IGARCH-N		IGARCH-ST		CS GARCH-N		CS GARCH-ST	
	5%	1%	5%	1%	5%	1%	5%	1%	5%	1%	5%	1%	5%	1%	5%	1%	5%	1%	5%	1%	5%	1%	5%	1%
	KFTX												Financial services											
Expectedex-ceeded	25.2	5	25.2	5	25.2	5	25.2	5	25.2	5	25.2	5	25.2	5	25.2	5	25.2	5	25.2	5	25.2	5	25.2	5
ActualVaRex-ceeded	36	20	39	15	34	17	37	6	37	20	40	17	38	14	39	9	27	13	35	7	33	13	33	8
Actual %	7.1	4	7.7	3	6.7	3.4	7.3	1.2	7.3	4	7.9	3.4	7.5	2.8	7.7	1.8	5.3	2.6	6.9	1.4	6.5	2.6	6.5	1.6
LR. UC stat	4.28	25.61	6.81	12.959	4.35	14.1	5.07	6.5	5.07	25.605	7.76	17.685	5.91	10.8	6.807	2.53	0.125	8.81	3.56	1.478	2.29	8.81	2.29	1.48
(p-value)	−0	0	−0	0	−0	0	−0	−0.8	−0	0	−0	0	−0	−0	−0.01	−0.1	−0.72	−0	−0.06	−0.52	−0.1	−0	−0.1	−0.2
Reject H0	YES	YES	YES	YES	YES	YES	YES	NO	YES	YES	YES	YES	YES	YES	YES	NO	NO	YES	NO	NO	NO	YES	NO	NO
LR. CCI stat	4.438	27.05	6.81	13.508	6.42	17.5	5.3	7.6	5.3	27.048	8.34	18.685	7.48	14.5	8.124	4.68	3.698	13.1	4.56	4.062	3.77	13.1	3.77	4.06
(p-value)	(0.191)	0	−0	−0.01	−0	0	−0.2	−0.6	−0.1	(0)	0	0	−0	−0	−0.02	−0.1	−0.16	−0	−0.1	−0.13	−0.2	−0	−0.2	−0.1
Reject H0	NO	YES	YES	YES	YES	YES	NO	NO	NO	YES	YES	YES	YES	YES	YES	NO	NO	YES	NO	NO	NO	YES	NO	NO
	Capital Market												IT services											
Expectedex-ceeded	25.2	5	25.2	5	25.2	5	25.2	5	25.2	5	25 .2	5	25.2	5	25.2	5	25.2	5	25.2	5	25.2	5	25.2	5
ActualVaRex-ceeded	34	14	35	10	31	11	31	7	31	13	35	10	41	17	41	12	38	13	41	11	41	17	45	14
Actual %	6.7	2.8	6.9	2	6.1	2.2	6.1	1.4	6.1	2.6	6.9	2	8.1	3.4	8.1	2.4	7.5	2.6	8.1	2.2	8.1	3.4	8.9	2.8
LR. UC stat	2.89	10.81	3.56	3.813	1.29	5.07	1.29	0.7	1.29	8.812	3.56	3.813	8.77	17.7	8.772	6.97	5.908	8.81	8.77	5.298	8.77	17.7	13.3	10.8
(p-value)	−0.1	−0	−0.1	−0.051	−0.3	−0	−0.3	−0.4	−0.3	−0.003	−0.1	−0.051	−0	0	−0	−0	−0.02	−0	−0	−0.12	−0	0	0	−0
Reject H0	NO	YES	NO	NO	NO	YES	NO	NO	NO	NO	NO	NO	YES	YES	YES	YES	YES	YES	YES	NO	YES	YES	YES	YES
LR. CCI stat	2.94	11.61	3.65	4.218	5.37	6.3	1.87	0.9	1.87	9.5	3.65	4.218	9.5	20.1	9.495	21.7	6.224	13.1	9.5	6.743	9.5	20.1	14.8	14.9
(p-value)	−0.2	−0	−0.2	−0.121	−0.1	−0.1	−0.4	−0.6	−0.4	−0.009	−0.2	−0.121	−0	0	−0.01	0	−0.04	−0	−0.01	−0.04	−0	0	−0	−0
Reject H0	NO	YES	NO	NO	NO	YES	NO	NO	NO	YES	NO	NO	YES	YES	YES	YES	YES	YES	YES	NO	YES	YES	YES	YES
	Professional services												Software											
Expectedex-ceeded	25.2	5	25.2	5	25.2	5	25.2	5	25.2	5	25.2	5	25.2	5	25.2	5	25.2	5	25.2	5	25.2	5	25.2	5
ActualVaRex-ceeded	30	13	36	10	30	12	32	5.5	33	12	36	10	32	15	37	12	29	14	35	8	31	15	37	11
Actual %	5.9	2.6	7.1	2	5.9	2.4	6.3	1.1	6.5	2.4	7.1	2	6.3	3	7.3	2.4	5.7	2.8	6.9	1.6	6.1	3	7.3	2.2
LR. UC stat	0.089	8.812	3.28	3.813	5.32	6.97	1.76	3.8	2.29	6.97	3.28	3.813	1.758	13	1.375	6.97	0.561	10.8	3.56	3.813	4.3	13	3.06	5.29
(p-value)	(0.846)	−0	−0.4	−0.051	−0	−0	−0.2	−0.9	−0.1	(0.008)	−0.1	−0.051	(0.185)	0	−0.24	−0	−0.45	−0	−0.1	−0.65	−0	0	−0.1	−0
Reject H0	NO	YES	NO	NO	YES	YES	NO	NO	NO	YES	NO	NO	NO	YES	NO	YES	NO	YES	NO	NO	YES	YES	NO	NO
LR. CCI stat (p-value)	1.35	9.5	4.36	4.218	7.01	17.5	2.48	4.2	3.16	9.55	4.36	4.218	3.51	13.9	5.695	7.56	3.314	11.6	4.56	4.218	6.76	13.9	5.66	5.79
	−0.1	−0.01	−0.1	−0.121	(0.03)	0	−0.3	−0.1	−0.2	−0.006	−0.1	−0.121	−0.2	−0	−0.06	−0	−0.19	(0 .003)	−0.1	−0.12	−0	−0	−0.1	−0.1
Reject H0	NO	YES	NO	NO	YES	YES	NO	NO	NO	YES	NO	NO	NO	YES	NO	NO	NO	YES	NO	NO	YES	YES	NO	NO

Source: Compiled by the authors based on backtesting test.

Note: Accept (Reject) of null hypothesis: if LR value is lower (higher) than critical value; H0 (Poff test): correct exceedances with critical value for 5% (1%) = 3.841 (6.635); H0 (Christoffersen test): correct and independence of exceedances with critical values for 5% (1%) = 5.991 (9.21).

Table 4

Descriptive Statistics of Var Oof KFTX and Fintech Industries before and during COVID-19

Summary statistics	KFTX	Capital Market	Financial Services	IT Services	Professional Services	Software
Before COVID-19						
Mean	−2.3483	−2.2793	−4.0565	−2.6816	−2.3917	−2.9624
Std. Dev.	0.9651	0.8105	1.0420	1.1191	0.8978	1.0356
Skewness	−1.5860	−1.8143	−0.3943	−1.6250	−1.9971	−2.4714
Kurtosis	5.8720	8.0673	2.6239	6.1015	9.3807	11.772
Jarque–Bera	663.0135	1406.550	27.6404	730.7853	2051.865	3671.418
Probability	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
During COVID-19						
Mean	−3.6705	−3.5988	−6.7916	−4.5261	−3.4692	−4.0987
Std. Dev.	2.8754	3.0262	3.7512	3.20241	2.7054	2.7736
Skewness	−3.1512	−3.9478	−2.2353	−2.5847	−3.3743	−2.7826
Kurtosis	14.1313	20.5667	8.1473	10.0023	15.1954	11.2734
Jarque–Bera	3442.929	7804.952	978.0325	1593.215	4087.816	2091.975
Probability	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)

Source: Compiled by the authors.

during COVID-19. As a result, we highlight a significant increase in the average VaR series during COVID-19 compared to the pre-COVID-19 period. Similarly, we observe the same increase in the values of standard deviation, skewness, kurtosis, and Jarque-Bera during the COVID-19 period. These results explain that during the COVID-19 period, we can observe higher levels of risk in the US Fintech stock market.

Next, we study the spillover volatility between the VaR series of the global index (KFTX) and Fintech industries before and during the COVID-19 pandemic. The results are presented in *Table 5*. First, the total volatility spillover index during the COVID-19 period (72.30%) is much higher than the values in the pre-COVID-19 period (39.30%). This increase can be explained by the intensive volatility of various factors based on the uncertainties caused by the spread of COVID-19, such as investor irrationality and a decline in labor productivity (Goodell [27]). Second, results indicate the existence of several changes in the level-indices connectedness. Especially before COVID-19 period, services were the industry that received risks from others, with values equivalent to 75.3%, while during COVID-19 period, software was the most important industry that received the most risks from others, with values equal to 91.1%. In addition, before COVID-19, the KFTX index (197.8%) and Capital Market industry (11.7%) had the highest risk contribution to the system's Va R. During COVID-19, the global index and professional services industry had the highest risk contribution to others, with respective values equal to 324.6% and 70.6%, respectively. As concerning the results of net spillovers, the main net transmitters of risks during COVID-19 are the global index with a value equal to 270.8%, followed by the professional services industry (31%). Further, before COVID-19 period, services were the main net receivers of risks from others, with values equal to −69.8%; subsequently, capital markets (−35%) and professional services (−34.2%), and Software became the most important net receiver of risks from others, with values equal to (−89.2%). Therefore, this total connectedness analysis suggests that during this period of turbulence, there is evidence of high-risk distress among global and industry VaR series in the US Fintech industry. For example, Baker et al. [28] reveal that COVID-19 is the cause of several turbulences that caused high instability in global financial markets.

Table 5

Spillover Volatility Effects Among Var Series before and during COVID-19

	KFTX	Capital Market	Financial Services	It services	Professional services	Software	From Others
Before COVID-19							
KFTX	90.9	1.9	2	1.4	2.3	1.6	9.1
Capital Market	42.3	53.3	1.8	0.6	0.7	1.4	46.7
Financial Services	18.9	5	72.5	1.4	0.5	1.6	27.5
It services	70.2	0.3	0.6	24.7	2.5	1.6	75.3
Professional services	35.7	3.5	1.3	1.4	57.4	0.7	42.6
Software	30.7	1.1	0.1	0.7	2.3	65.1	34.9
Contribution to others	197.8	11.7	5.9	5.5	8.4	6.8	236
Contribution including own	288.8	65	78.4	30.2	65.7	71.9	39.30%
Net spillover	188.7	–35	–21.6	–69.8	–34.2	–28.1	
During COVID-19							
	KFTX	**Capital Market**	**Financial Services**	**It services**	**Professional services**	**Software**	**From Others**
KFTX	74.7	3.6	1.1	1.4	18.7	0.4	25.3
Capital Market	62	16.1	1.5	1.1	18.7	0.7	83.9
Financial Services	58.6	1.4	23.1	2.7	14	0.1	76.9
It services	68.1	1.8	0.7	10.8	18.5	0.1	89.2
Professional services	53.4	10.3	1.7	1.3	32.8	0.5	67.2
Software	53.9	4.7	2.3	2	28.3	8.9	91.1
Contribution to others	296.1	21.8	7.3	8.5	98.2	1.9	433.7
Contribution including own	370.7	37.9	30.4	19.3	130.9	10.8	72.30%
Net spillover	270.8	–62.1	–69.6	–80.7	31	–89.2	

Source: Compiled by the authors based on Diabold and Yilmaz index.

Figure 3 shows the dynamic connectedness among the VaR series of the US global index and each industry Fintech before and during COVID-19. Before COVID-19, the total volatility connectedness index decreased gradually from July 2016 between 50% and 40% until it achieved a minimum value equal to 34%. Accordingly, this decrease can be explained by the high tensions of the trade war between China and the USA in February 2018. From this point, the index returns to be stable between values equal to 50% and 45% until attaining a maximum value equal to 65% in September 2019. In addition, during COVID-19, the total spillover index presents a major rise in the first period of 2020, with level values nearly reaching 77%, indicating that this strong risk interaction was mentioned by the outbreak of COVID-19. Afterward, it started to decline and continued this decrease in the presence of calm and stressful moments until it achieved a minimum value of 48% at the end of 2021.

CONCLUSION

The main objective of this paper is to test the accuracy of GARCH models to estimate and forecast the VaR of the US Fintech global stock market from July 20, 2016, to December 31, 2021. In addition, this study examines the impact of the COVID-19 crisis on the connectedness between the adequate VaR of each US global KFTX index and five Fintech industries. Specifically, we compare the different VaR estimates (862 in-sample daily returns) and one-day-ahead forecasts (550 out-

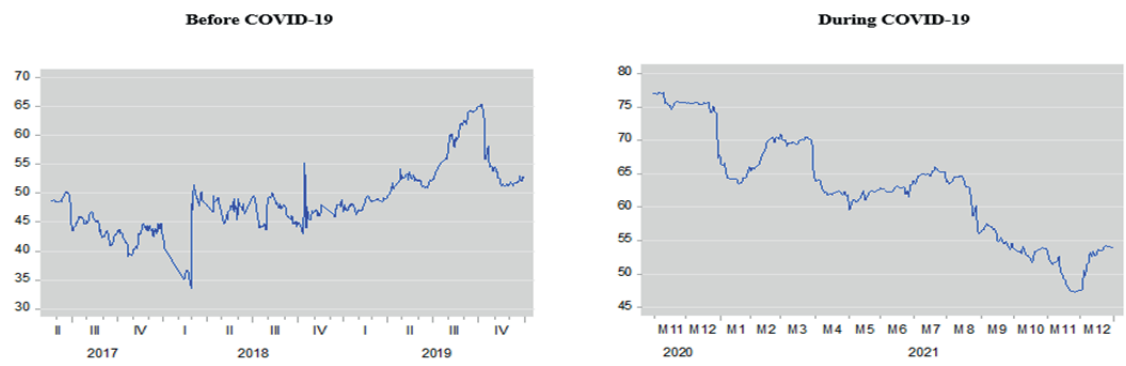

Fig. 3. **Correlogram Plot of Pairwise Correlation Among Var of Global and Industrials Series Before and During COVID-19**

Source: Compiled by the authors.

of-sample daily returns) of several GARCH model specifications under a normal distribution and Student-T distribution with 1% and 5% significance levels. We estimate the I-GARCH, S-GARCH, and CS-GARCH models using a backtesting test based on the procedures of Kupiec and Christoffersen.

The empirical results show that the GARCH models under the student-t distribution perform better than the normal distribution before and during the COVID-19 periods. Moreover, the backtesting results before (during) COVID-19 do not reject the null hypothesis of the complementary tests for all GARCH models under student-t distribution with $\alpha = 1\%$ and $\alpha = 5\%$ (only with $\alpha = 1\%$) in most cases. Then, by comparing the occurrence of exceedances between these models before and during COVID-19, we can state that the I-GARCH model outperforms the other GARCH specifications based on the Student-t distribution with $\alpha = 1\%$. This model gives superior results for its accuracy in correct exceedance coverage and failure independence. Therefore, this model performs best in both calm and crisis periods in the US Fintech industry. Finally, to capture the effect of COVID-19 on the connectedness between the VaR series (I-GARCH), we study the volatility spillover index between the VaR of the US Fintech index and each industry before and during COVID-19. The empirical results revealed a sharp increase in the volatility spillover index among the VaR series during COVID-19. In addition, the main net transmitters of risks during COVID-19 are the global index with a value equal to 270.8%, followed by the professional services industry (31%). While software was the main net receiver of risks from others before COVID-19.

Therefore, our results indicate that VaR is a suitable indicator to manage and measure the risk of the global US Fintech index and individual US Fintech industries. In addition, our results highlight the best performing I-GARCH-VaR model in both calm and crisis periods, which can satisfy investors' requirements. More precisely, the estimation and forecasting of VaR results could be helpful for investors and portfolio managers where their portfolio VaR could be greatly affected by the COVID-19 pandemic. On one hand, investors aim to diversify their investment decisions' portfolio in Fintech market risk by purchasing the titles that reduce the portfolio risk (VaR) and selling the titles that raise the portfolio risk (VaR), especially, during financial crises. On the other hand, portfolio managers could hedge their portfolio risk by managing their portfolio dynamically during a crisis period. In addition, our results give insights for risk regulators who may consider earlier the extreme connectedness among the US Fintech industries and its potential change in stress periods.

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O. Gharbi — statement of the problem, development of the concept of the article, collection of statistical data, formation of tables and figures, description of the results.
M. Boujelbène — critical analysis of literature, description of the results and the formation of conclusions of the study.
R. Zouari— econometric modeling.

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