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Comparison of Systemic Financial Risks in the US before and after the COVID-19 Outbreak—A Copula–GARCH with CES Approach

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Abstract: The analysis and prediction of systemic financial risks in the US during the COVID-19 pandemic is of great significance to the stability of financial markets in the US and even the world. This paper aims to predict the systemic financial risk in the US before and during the COVID-19 pandemic by using copula–GJR–GARCH models with component expected shortfall (CES), and also identify systemically important financial institutions (SIFIs) for the two comparative periods. The empirical results show that the overall systemic financial risk increased after the outbreak of the COVID-19 pandemic, especially in the first half of the year. We predicted four extreme risks that were basically successful in capturing the high risks in the US financial markets. Second, we identified the SIFIs, and depository banks made the greatest contribution to systemic risk from four financial groups. Third, after the outbreak of the epidemic, the share of Broker–Dealer and Other Institutions in the overall systemic risk has apparently increased. Finally, we recommend that the US financial regulators should consider macro-prudential guidance for major financial institutions, and we should pay more attention to Broker–Dealers, thereby improving the financial stability of the US and the global financial markets.

Keywords: CES; copula; systemic risk; GARCH; financial crisis

MSC: 62P05; 62P20; 62P25

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1. Introduction

As the integration of global financial markets continues to deepen, systemic financial risk and its impact on the financial markets has been widely considered. The United States (US) is the largest economy in the world, and its GDP accounted for 24% of the world economy in 2019 [1], as well as the largest financial market in the world. It is no doubt that the US can have a large impact on the global economy and financial markets. The latest data from Statistia show that the total assets of financial institutions in the United States were approximately USD 123 trillion in 2020, accounting for 26.3% of the total assets of global financial institutions. The US's dominance in global financial markets is unshakable because it is the largest economy and the largest financial market, and it has the largest holdings of stocks of foreign assets and liabilities, the most important currency, and the most important form of safe asset (US debt) in the world [1]. In view of the special position of the US financial market and the position that it is too big to fail, systemic financial risk in the US has been widely studied by scholars, especially during extreme events, such as financial crises and energy crises [2–6]. All scholars and researchers generally believe that the prediction and analysis of systemic financial risks in the US is of great significance, especially conducive to preventing financial risks and playing an early warning role for global financial risks.

The outbreak of the COVID-19 epidemic has severely shaken global financial markets. Obviously, this epidemic has had a dramatic impact on the stock markets, futures markets, and bond markets of various countries for more than two years, since the beginning of 2020 [7–12]. In particular, the US financial market has been greatly impacted, thus increasing the risk of the global financial market [13,14]. The outbreak of COVID-19 was a catastrophic event and is likely to materialize as the Great Lockdown Recession. It represents one of the steepest recessions since the Great Depression of the 1930s [15]. US real GDP fell from 2.3% in 2019 to −3.4% in 2020, while the unemployment rate rose to 8.1% in 2020 from 3.7% in 2019. The epidemic had a significant impact on the financial markets, and the valuation of banks and financial institutions fell by almost 39%. The Dow Jones Index fell sharply on 12 and 16 March 2020, to 9.99% and 12.9%, respectively, which were the two largest consecutive single-day falls in the US stock market since Black Monday in 1987. It can be seen that we should strengthen the research on systemic financial risks in the United States during the COVID-19 epidemic. According to the theory of too big to fail, the identification of major risk institutions during the COVID-19 is also very worthy of study. After the 2008 financial crisis, systemic financial risks have been widely studied, and several measurement methods have emerged. Acharya et al. [2,16] proposed a helpful approach of the marginal expected shortfall (MES) to measure the level of systemic risk. However, MES does not take into account the size and influence of companies in terms of the too big to fail paradigm. Therefore, the Systemic Risk indices (SRISK) method was extended to include MES to assess the size effect and leverage of the financial institution to measure systemic risk [4], and it can be calculated by daily data with a higher frequency at no additional cost. The drawback for SRISK is that it must be based on the qualified assumption that the company's liabilities are constant, and it may cause a bias prediction [3]. Banulescu and Dumitrescu [3] improved and developed this approach into the component expected shortfall (CES) approach by taking advantage of SRISK. The CES can measure the absolute value that financial firms contribute to systemic risk by taking into account the impact of company size and leverage; in addition, CES relaxes the constant maturity assumption of corporate liabilities. The sum of the CES values of companies corresponds to the gross value of the CES of the entire financial market, which simply, intuitively, and accurately reflects the actual situation of the financial market. These features of the CES approach are beneficial for financial market regulators to oversee the large institutions that create systemic risk. We have found that most research on the US financial market risks during the epidemic focuses more on the risk of the epidemic spilling over into the US financial markets [13,17]) and the risk of the US financial markets spilling over into other economies or global financial products [7,18,19]. However, research on the major financial institutions that contribute to the systemic risk of the US financial market is insufficient.

Since the beginning of 2020, a tremendous amount of research has been conducted on the connections between the COVID-19 epidemic and financial markets. Many studies have focused on the impact of the COVID-19 outbreak on financial markets [9,14,20–22]. There have also been studies examining systemic risks in different regions and countries due to the outbreak [9,17,23]. Research on financial system risks in international futures markets such as gold and crude oil, foreign exchange markets, and bond markets has also attracted attention during the epidemic [18,24,25]. It can be seen that research on financial risk has had importance during the epidemic.

Applied research to measure and forecast financial risk typically begins with the US financial market and extends to global financial markets. Engle [26] recognized correlations among US financial indices, US bonds, and foreign currency changes over time and proposed a new measure to improve the assessment and forecasting of financial risks during the financial crisis. Kupiec [27] conducted stress tests on US financial institutions to measure the potential losses of these financial institutions. Financial risk spillovers and financial systemic risk are two main issues of concern in the US financial market. Before the outbreak of the epidemic, many studies focused on risk spillovers from US financial markets to global financial markets [28,29]. Risk spillover effects of unconventional monetary policy on US financial markets have been examined [30,31]. Many new approaches have been proposed to analyze the impacts of risk spillovers on US financial institutions during the US financial crisis on the US financial market [3,32,33]. At the same time, other studies have focused on analyzing the financial systemic risk, which is a measure of a single company's risk contribution to the overall US financial system, and identifying the major financial institutions during the global financial crisis [3,5,16]. Empirical results from US financial markets showed that most systemic risk is concentrated in a few institutions and verified more accurate measures of each company's contribution to expected profits and losses of financial institutions. After the outbreak of the COVID-19 epidemic, numerous studies focused on the impact of risk transfers either from the COVID-19 epidemic to US financial markets [13,15,22] or from US financial markets to global financial markets [17]. We see the importance of the US financial market, especially when examining financial risks. However, we found that there is a lack of research on financial systemic risk after the outbreak of COVID-19 epidemic.

Dependence analysis is important for effective risk management and portfolio management [8]. Many studies [3,32,34,35] used dynamic conditional correlation-generalized autoregressive conditional heteroskedasticity (DCC–GARCH) models to estimate linear correlations of financial assets and further measure financial risk. However, many scholars have verified that nonlinear correlation and tail correlations are more favored between financial assets [8,36,37]. Because linear correlation cannot capture the tail correlation and asymmetric dependence of financial assets, the DCC–GARCH approach may underestimate risk [38–40]. Therefore, we use the copula–GARCH models with CES and the DCC–GARCH models with CES to estimate the systemic risk of the US financial market. It may be a better way to see what is the difference of the systemic risk that is influenced by nonlinear correlation.

Our contribution to literature can be summarized into three points. First, we analyzed and predicted the systemic financial risk of the US financial market during the COVID-19 pandemic by using the CES approach based on linear and nonlinear dependence. We found that the systemic risk increased significantly after the outbreak of the epidemic. The top 10 systemically important financial institutions (SIFIs) contributed more than 90% of the risk. Second, the identification of the main risk contributors among US financial firms before and during the epidemic is one of the contributions to this paper. Specifically, in the early phase of the outbreak, the top 10 SIFIs identified JPMorgan, Bank of America, Wells Fargo, Citigroup, American Express, Morgan Stanley, Charles Schwab Corporation, BlackRock, Goldman Sachs Group, and SP Global Inc. These 10 firms account for 55% of all 55 companies in terms of market capitalization, which confirms the predicted accuracy of CES. Third, we found the difference between the DCC–GARCH and the copula–GARCH models in predicting systemic risk in the US financial market. The linear dependency model to some extent underestimated the risk before the epidemic and somehow overestimated the risk during an extreme event. Such shortcomings can be solved by nonlinear dependency.

The remainder of this paper is organized as follows: Section 2 describes the methods that are employed in the paper, and Section 3 presents the descriptive data. In Section 4, we present the empirical results. The conclusions are presented in Section 5. In this paper, we conducted the data processing and analysis by imposing R software (version 4.2.2) with the rugarch, CDvine, and PerformanceAnalytics packages.

2. Methodology

In this study, the two-step estimation method is used to estimate the copula–GJR–GARCH models and the DCC–GJR–GARCH models. In the first step, we filter the financial data by using the GJR–GARCH models, and thus obtain the standardized residuals of the financial data. Hereafter, the copula–GARCH and the DCC–GARCH are used to estimate dependence structure of the financial asset. On the basis of these two models, CES method is applied to analyze systemic financial risk. In this section, we first introduce the GJR–GARCH models, and then discuss the copula functions and tail dependence. Subsequently, the DCC–GARCH models and forecasting process of systemic financial risk are presented.

2.1. GJR–GARCH

The financial series sometimes have the feature of a leverage effect. It can be measured by an asymmetric reaction of volatility with negative shocks or positive shocks of the same magnitude. Glosten et al. [41] used the GJR–GARCH model to analyze negative shocks on the conditional variance asymmetrically by imposing the indicator function. The variance equation of the GJR–GARCH can be expressed as

$$\sigma_t^2 = \omega + \alpha\varepsilon_{t-1}^2 + \beta\sigma_{t-1}^2 + \gamma I_{t-1}\varepsilon_{t-1}^2, \tag{1}$$

where ω, α, β, and γ are parameters, and γ represents the leverage effect. The indicator function I_{t-1} takes the value 1 if $\varepsilon_{t-1} \leq 0$ and 0 otherwise.

2.2. Copula and Tail Dependence

2.2.1. Sklar's Theorem

The copula function is one kind of joint distribution function. Bivariate copula is used to link two marginal distributions. Different copula families can capture the different dependence structures and/or tail dependence. For given univariate marginal distribution functions $F_1(x_1), F_2(x_2)$ of variables x_1, x_2, the bivariate distribution function C is defined as a copula function in the following equation:

$$C(F_1(x_1), F_2(x_2)) = F(x_1, x_2). \tag{2}$$

Sklar [42] proved the following properties for a copula function: If $F(x_1, x_2)$ is a joint bivariate distribution function with univariate marginal distribution functions $F_1(x_1)$, $F_2(x_2)$, then there exists a copula function $C(u_1, u_2)$ such that $F(x_1, x_2) = C(F_1(x_1)\,,\, F_2(x_2))$. We have conducted financial modeling with copula functions in past years, with the related applications of copula functions in financial fields, including financial markets contagion, risk integration to default correlations, and capital allocation.

2.2.2. Rank Correlation

In the context of studying dependency structure, Kendall's τ is a measure of rank correlation reflecting monotonic dependency [43]. If margins are normal distributions, parameters in the Gaussian copula and Student-*t* copula usually represent the Pearson linear correlation coefficient (ρ). In contrast, Kendall's τ is used to reflect a nonlinear dependence in Archimedean copulas. In addition, the Gaussian copula is symmetric and without tail dependence. The *t*-copula is symmetric, but the tail dependence can be measured. The survival Gumbel copula, the survival BB1 copula, and the survival BB8 copula are asymmetric with an upper tail, a lower tail, or both.

2.2.3. Tail Dependence

A tail dependence analysis related copula model provides a method to measure the probability that two assets are in the lower or upper joint tails of a bivariate distribution. The upper and the lower tail dependence, proposed by Joe [43], can be expressed in Equations (3) and (4) as follows:

$$\lambda_U = \lim_{u \to 1^-} \Pr\left[X \geq F_X^{-1}(u) \mid Y \geq F_Y^{-1}(u)\right] = \lim_{u \to 1^-} \frac{1 - 2u + C(u,u)}{1-u} \tag{3}$$

$$\lambda_L = \lim_{u \to 0^+} \Pr\left[X \leq F_X^{-1}(u) \mid Y \leq F_Y^{-1}(u)\right] = \lim_{u \to 0^+} \frac{C(u,u)}{u} \tag{4}$$

where $F_X^{-1}(u)$ and $F_Y^{-1}(u)$ are the marginal quantile functions, and λ_U and $\lambda_L \in [0,1]$ denote the upper and the lower tail dependence of a joint bivariate distribution, respectively.

Traditionally, econometric models for financial risk research typically assume a multivariate normal distribution with a linear dependency structure to describe the correlation between asset returns, such as the DCC–GARCH. However, numerous empirical studies have shown that skewed, kurtosis, fat-tail, and nonlinear joint distributions are more realistic for real-world circumstances [37–39]. We randomly simulated data from different Copula families with different marginal distributions to compare the traditional ones (see Figure 1). Comparing the two columns, we can see that the marginal distribution of the skewed Student-*t* (SSTD) can capture some more extreme data. In contrast, looking at the rows, one can observe that survival Gumbel and survival BB8 captured lower tail correlation well, survival BB1 performed well on upper tail, and Student-*t* measured both upper and lower tail correlation symmetrically. Although only part of the simulation was shown in our research, we were able to draw an inference that many different copula families and marginal distributions are suitable for fitting correlation under different circumstances. Therefore, we need many marginal distributions and copula families to ensure that the target joint can be optimally fitted.

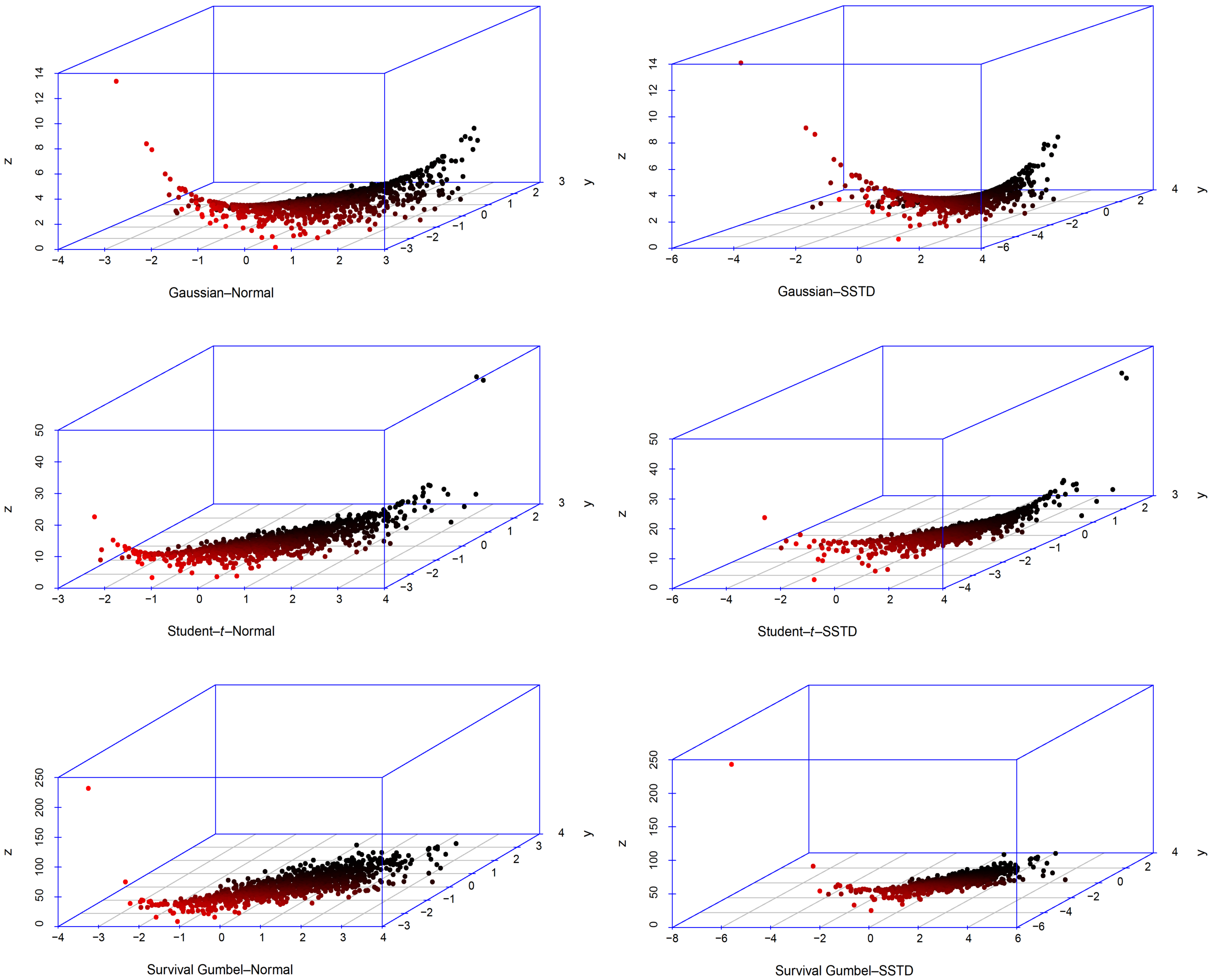

Figure 1. *Cont.*

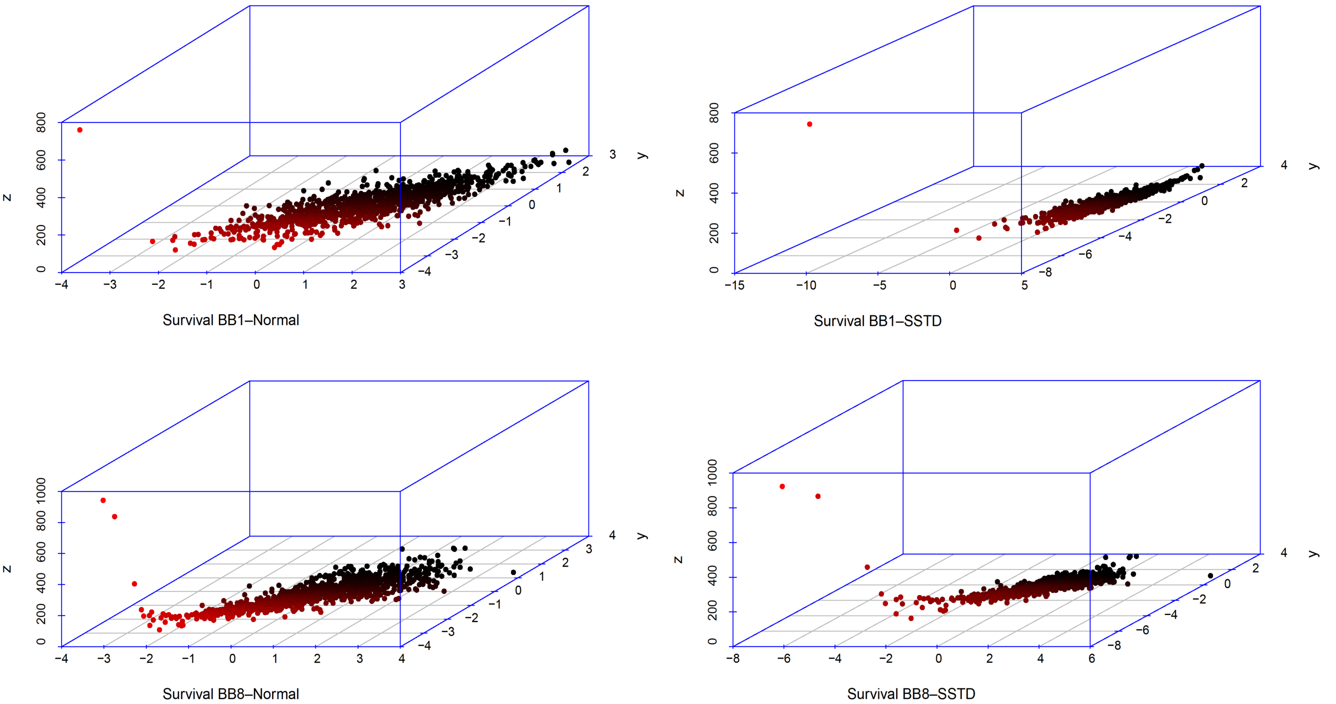

Figure 1. Three–dimensional plots based on Gaussian copula, Student-*t* (5) copula, survival Gumbel copula, survival BB1 copula, and survival BB8 copula under the dependence parameter, $\tau = 0.5$, with two types of marginal distributions (Normal (0, 1) and SSTD (0.8, 5)).

2.3. DCC–GARCH

Banulescu and Dumitrescu [3] used the DCC–GARCH to measure systemic risk. In order to compare the practical effect on measuring the systemic risk between DCC–GARCH and Copula–GARCH, the DCC–GARCH model [4] is used as the benchmark model, as follows:

$$r_t = H_t^{1/2} \varepsilon_t \tag{5}$$

where $r_t = (r_{mt}, r_{it})'$ represents the transposed vector of returns from market and firms, and $\epsilon_t = (\varepsilon_{mt}, \xi_{it})'$ indicates the transposed vector of i.i.d. shocks that have zero mean and identity covariance matrix; H_t is the conditional covariance matrix of time-varying

$$H_t = \begin{pmatrix} \sigma_{mt}^2 & \sigma_{mt}\sigma_{it}\rho_{it} \\ \sigma_{mt}\sigma_{it}\rho_{it} & \sigma_{it}^2 \end{pmatrix} \tag{6}$$

where σ_{mt} and σ_{it} represent the market and the firms on their conditional standard deviations, respectively, and ρ_{it} is the time-varying conditional correlation.

2.4. Component Expected Shortfall

The expected shortfall (ES) is considered in this study as representing the overall risk of the financial system. We use the ES to measure the expected aggregate loss conditional on the return smaller than the β quantile,

$$ES_{m,t-1}(V) = -E_{t-1}(r_{mt} \mid r_{mt} < V) \tag{7}$$

where V stands for the threshold value. In general, the V value is the value-at-risk (VaR) for the portfolio. Therefore, V can be defined as being equal to $\mathrm{VaR}_\beta(W)$. CES can be utilized to measure the risk on an enterprise with its absolute contribution of the financial system [3]; the systemic risk can be measured by linearly aggregating the component losses as well. Following Banulescu and Duitrescu [3] and Liu et al. [38], the formulas of systemic risk, CES, are given as follows:

$$CES_{it} = w_{it}\frac{\partial ES_{m,t-1}\left(\mathrm{VaR}_{\beta}(W)\right)}{\partial w_{it}} \tag{8}$$

$$CES\%_{it}\left(\mathrm{VaR}_{\beta}(W)\right) = \frac{\mathrm{CES}_{it}\left(\mathrm{VaR}_{\beta}(W)\right)}{SES_{t-1}\left(\mathrm{VaR}_{\beta}(W)\right.} \times 100 \tag{9}$$

$$SES_{t-1}\left(\mathrm{VaR}_{\beta}(W)\right) = \sum_{i=1}^{n} CES_{it}\left(\mathrm{VaR}_{\beta}(W)\right) \tag{10}$$

where W is the portfolio allocation, $\mathrm{VaR}_{\beta}(W)$ is the VaR under the β confidence level, and $CES\%_{it}$ is the percentage risk contribution of firm i to the whole system at period t. A larger $CES\%_{i}$ implies that it is more systemically important for institution i. Equations (8) and (9) can be used to calculate the absolute contribution of an institution, and the systemic risk can be measured under given weights. In this study, each index has equal weight.

2.5. Forecasting Process for Systemic Risk

As for out-of-sample forecast of the systemic risk, Banulescu and Dumitrescu [3] adopted the following equation:

$$CES\%_{i,T+1:T+h}(\tilde{C}) = \frac{CES_{i,T+1:T+h}(\tilde{C})}{\sum_{i=1}^{n} CES_{i,T+1:T+h}(\tilde{C})} \times 100 \tag{11}$$

where $\tilde{C}$ is set to be the out-of-sample VaR-HS for cumulative market returns at coverage rates of 1%, and h represents the forecasting horizon. The rolling window and the Monte Carlo simulation approach based on the copula–GARCH model and the DCC–GARCH model were used to implement the one-step-ahead forecasts of CES.

Forecasting the significant firms' contribution to systemic risk is fairly important for policy decisions. Consider that the aim is to forecast the systemic risk of the financial institution i over a future period that ranges between the dates $T+1$ and $T+h$, where h is the forecast horizon. The forecasting is implemented by both the copula–GARCH and the DCC–GARCH approaches.

Forecasting by Copula—GARCH

The process based on copula–GARCH can be conducted by following four steps:

i. Simulate 10,000 random numbers based on the best fit copula model;
ii. Obtain the standardized residuals by imposing the inverse function of the corresponding variables with their marginal distribution;
iii. Use the GARCH model to forecast the value in the $T+1$ period, which means 10,000 simulated values should be generated as in the following equation:

$$R^{S}_{k,T+1,T+h} = \exp\left(\sum_{j=1}^{h} r^{s}_{k,T+j}\right) - 1, k = \{m, i\} \tag{12}$$

where $r^{s}_{k,T+j}$ is the series of returns corresponding to the sth path of the market if $k = m$ and of institution i if $k = i$. The S sequence is considered for each asset so as to obtain the $(S, 1)$ vector of cumulated returns.
iv. Estimate the long-run MES with

$$\mathrm{MES}_{i,T+1:T+h}(\tilde{C}) = \frac{\sum_{s=1}^{S} R^{S}_{i,T+1:T+h^{S}I}\left(R^{S}_{m,T+1:T+h} < \tilde{C}\right)}{\sum_{s=1}^{S} I\left(R^{S}_{m,T+1:T+h} < \tilde{C}\right)} \tag{13}$$

where $\tilde{C}$ represents the threshold as the systemic event in out-of-sample [16]. They might alter according to the forecast range.

After the MES$(\tilde{C})$ is obtained for every single firm, the systemic risk for out-of-sample can be expressed by

$$CES\%_{i,T+1:T+h}(\tilde{C}) = \frac{CES_{i,T+1:T+h}(\tilde{C})}{\sum_{i=1}^{n} CES_{i,T+1:T+h}(\tilde{C})} \tag{14}$$

where $CES_{i,T+1:T+h}(\tilde{C}) = w_{iT} MES_{i,T+1:T+h}(\tilde{C})$ and w_{iT} are the weights of the i-th firm in the financial system at time t.

Forecasting by the DCC–GARCH

The DCC–GARCH forecasting will be the same as the studies by Brownlees and Engle [4] and Banulescu and Dumitrescu [3]. It is mostly the same as the copula approach except for the first two steps, which are as follows:

i. Simulate 10,000 random numbers based on best fitting the DCC–GARCH model;
ii. Obtain the standardized residuals by imposing the inverse function on the corresponding variable with its marginal distribution;
iii.,iv. Refer to the aforementioned copula–GARCH approach.

3. Data

We selected a few financial companies from the SP500 companies to represent the US financial market. The data retrieval process consisted of three steps. First, 60 financial institution tickers were retrieved from the SP500 and data validity was checked to get the daily stock price. This is because Yahoo Finance provided an adjusted stock price, meaning that along with the price it remains a fixed outstanding and market capital change. It is easy to prove that all 60 companies have a market cap of over USD 5 billion as of 26 September 2017. Second, the 60 financial institutions were divided into four groups according to the Standard Industrial Classification (SIC) [16]. The four classifications are Depositories, Insurances, Broker–Dealers, and Others (refer to abbreviations). Third, based on the companies listed by Banulescu and Dumitrescu [3], a new approach was taken to target the financial companies, as some of them had closed or had provided incomplete information. All financial companies from SP500, with a total of 68 companies (to search date 27 August 2017), were selected, and 60 companies were confirmed for the final target list based on data completeness and availability (see Table 1 for pre-COVID-19 period). However, the number of target companies shrank to 55 companies during the COVID-19 period for a similar reason. (According to the US Standard Industrial Classification (SIC) code, the 60 firms have been classified into four groups in terms of depositories banks (SIC code 60), insurance companies (SIC code 63, 64), brokers–dealers (SIC code 6211), and other financial institutions (SIC code 61, 62, excluding 6211). The companies have been categorized in the Table 1 according to the new standard.)

In general, the financial firms and their classifications remain consistent with Banulescu and Dumitrescu [3], but there were three differences: (1) The total number of target financial firms decreased from 74 firms to 60 firms. (2) COF and FITB (depository banks) and TROW (other financial institution) have changed to the classification of brokers–dealers under the new SIC code [3]. In addition, formerly a broker–dealer, MMC changed its classification to an insurance company. (3) Many financial firms merged: for example, insurance firms such as L, MET, PFG, PRU, and RE; broker–dealer firms such as AJG, AON, RJF, and WLTW; and other financial institutions such as AMG, AMP, CME, DFS, ICE, IVZ, LUK, MCO, NDAQ, and SPGI. Apart from the firms noted above, the other companies listed in this paper agreed with Banulescu and Dumitrescu [3]. Finally, it can be seen that the share price provided by Yahoo Finance has been adjusted by unifying the coherent outstanding share amounts. The historical price can be set directly and easily without worrying about the impact of stock splits and stock consolidations.

Table 1. Dataset.

	Depository (18)	Market Cap		Insurance (18)	Market Cap
BAC	Bank of America Corp.	372.1	AFL	AFLAC Inc.	41.2
BBT	BBT Corporation	-	AIG	American International Group Inc.	51.0
BK	The Bank of New York Mellon Corp.	46.1	AIZ	Assurant Inc.	9.5
C	Citigroup Inc.	128.4	ALL	Allstate Corp.	34.4
CMA	Comerica Inc.	12.7	CB	Chubb Limited	84.8
COF	Capital One Financial	63.9	CINF	Cincinnati Financial	20.2
FITB	Fifth Third Bancorp	32.9	HIG	Hartford Financial Svc. Gp.	23.7
HBAN	Huntington Bancshares	22.8	L	Loews Corp.	15.1
JPM	JPMorgan Chase Co.	445.8	LNC	Lincoln National	12.5
KEY	KeyCorp	23.9	MET	MetLife Inc.	57.6
MTB	MT Bank Corp.	23.5	PFG	Principal Financial Group	19.0
NTRS	Northern Trust Corp.	24.6	PGR	Progressive Corp.	61.5
PBCT	People's United Financial	8.9	PRU	Prudential Financial	43.2
PNC	PNC Financial Services	84.5	RE	Everest Re Group Ltd	11.9
RF	Regions Financial Corp.	22.5	TMK	Torchmark Corp.	-
STT	State Street Corp.	34.3	TRV	The Travelers Companies Inc.	41.1
USB	US Bancorp	84.8	UNM	Unum Group	5.8
WFC	Wells Fargo	218.2	XL	XL Capital	-
		1649.9			532.5
	Broker–Dealer (9)	**Market Cap**		**Others (15)**	**Market Cap**
AJG	Arthur J. Gallagher Co.	32.0	AMG	Affiliated Managers Group Inc.	5.7
AON	Aon PLC	60.4	AMP	Ameriprise Financial	33.2
ETFC	E * Trade	-	AXP	American Express Co.	148.6
GS	Goldman Sachs Group	116.4	BEN	Franklin Resources	15.1
MMC	Marsh McLennan	76.2	BLK	BlackRock	115.7
MS	Morgan Stanley	170.4	CME	CME Group Inc.	85.8
RJF	Raymond James Financial Inc.	22.6	DFS	Discover Financial Services	35.4
SCHW	Charles Schwab Corporation	162.6	HRB	Block HR	4.1
WLTW	Willis Towers Watson	28.9	ICE	Intercontinental Exchange	69.2
			IVZ	Invesco Ltd.	10.3
			LUK	Leucadia National Corp.	-
			MCO	Moody's Corp.	60.0
			NDAQ	Nasdaq Inc.	28.7
			SPGI	SP Global Inc.	92.0
			TROW	T. Rowe Price Group	32.9
		669.5			736.7

* The values of market capitalization of financial firms were requested on 18 February 2022 and were in billion USD. Five institutions (BBT, TMK, XL, ETFC, and LUK) were not listed on the requested day and have not been on since then.

The target research period of the daily data was from 5 January 2010 to 30 December 2021 with two scenarios of pre-COVID-19 and during COVID-19; see Table 2. Pre-COVID-19 covers the period from 5 January 2010 to 30 June 2017 with 1886 observations. The in-sample period was from 5 January 2010 to 30 June 2015 with 1381 observations, and the out-of-sample period was from 1 July 2015 to 30 June 2017 with 505 observations. Scenario during COVID-19 imposed comparative data from 1 July 2017 to 30 December 2021 with 1133 observations. The in-sample period was from 1 July 2017 to 31 December 2019 with 629 observations, and the projected period was from 2 January 2020 to 30 December 2021 with 504 observations. Typically, regulators are more interested in the overall risk contribution over a specific time period rather than for a specific date, so each two-year forecast period before and after the outbreak is divided into four periods for comparison.

Table 2. Eight forecasting periods before and during COVID-19 epidemic.

Period	Before COVID-19	Period	COVID-19
Stage 1	1 July 2015–31 December 2015	Stage 5	3 January 2020–30 June 2020
Stage 2	4 January 2016–30 June 2016	Stage 6	1 July 2020–31 December 2020
Stage 3	1 July 2016–30 December 2016	Stage 7	4 January 2021–30 June 2021
Stage 4	3 January 2017–30 June 2017	Stage 8	1 July 2021–30 December 2021

4. Empirical Analysis

4.1. Volatility Analysis with Asymmetric Effect

The larger value of γ indicates the higher leverage effect of the equity price, and the top 10 ranked companies are shown in Table 3. There are two insurance companies, three broker–dealer companies, and five other companies among the top 10. The magnitude of β can explain long-run volatility for a stock return. A magnitude over 0.8 is considered to indicate long-run volatility. It can be seen that all of the top 10 companies fulfill the property of long-run volatility.

Table 3. Top ten in asymmetric effect ranking among sixty financial institutions.

Ranking	Institution	Type	α	β	γ
1	AMP	Other	0.0000	0.8633	0.2160
2	MCO	Other	0.0357	0.8492	0.2063
3	MMC	Broker–Dealer	0.0000	0.8770	0.1990
4	AMG	Other	0.0000	0.9004	0.1864
5	TMK	Insurance	0.0136	0.8836	0.1825
6	IVZ	Other	0.0130	0.8884	0.1614
7	BLK	Other	0.0142	0.8760	0.1545
8	L	Insurance	0.0059	0.8836	0.1435
9	AON	Broker–Dealer	0.0248	0.8757	0.1404
10	AJG	Broker–Dealer	0.0549	0.8151	0.1375

4.2. Kendall's τ and Tail Dependence

We applied 40 copula families to fit all pairs of the market return and the 60 listed companies. The best fit of copula families were selected by AIC. Table 4 shows the top 10 Kendall's τ dependence ranking of the US financial institutions and the financial market. The tail dependencies for those institutions are also displayed. The top ten companies include all the four types of companies: two insurance companies, one broker–dealer company, six depository companies, and one other company. This implies that the depository industry has a higher dependence with the US financial market. We may infer that once the depository bank is risky, the financial market is also very likely to incur risk. For the top 10 among the 60 companies, only MS was best fitted by the survival BB1 copula, and the remaining nine companies were fitted by the Student-t copula. That is, there were nine companies that had symmetrical tail dependence structures on the overall financial market, and there was an asymmetric tail dependence in one pair. The values of Kendall's τ of the bivariate copula functions reveal the rank correlations between the listed companies and the market. The top 10 ranking companies with the highest correlations were JPM, WFC, C, BAC, MS, PRU, MET, PNC, AMP, and BK. Comparatively, those companies account for larger shares, which makes them have a relatively high correlation with the market. The tail correlation values of most of those companies were greater than 0.5, which explains why the top 10 listed companies are closely linked with the bull market and the bear market.

Table 4. Top 10 dependence ranking and tail dependencies of US financial institutions.

Ranking	Institution	Type	Family	τ	λ_u	λ_l
1	JPM	Depository	T	0.7043	0.5910	0.5910
2	WFC	Depository	T	0.6842	0.5381	0.5381
3	C	Depository	T	0.6792	0.5129	0.5129
4	BAC	Depository	T	0.6721	0.5003	0.5003
5	MS	Broker–Dealer	Survival BB1	0.6387	0.2085	0.6872
6	PRU	Insurance	T	0.6381	0.5364	0.5364
7	MET	Insurance	T	0.6342	0.4887	0.4887
8	PNC	Depository	T	0.6310	0.5189	0.5189
9	AMP	Other	T	0.6251	0.5056	0.5056
10	BK	Depository	T	0.6245	0.4848	0.4848

4.3. Forecasting of the Systemic Financial Risk

Table 5 shows the out-of-sample CES ranking based on the bivariate copula–GARCH and the DCC–GJR–GARCH models. The values of the CES revealed the absolute contribution of the listed companies to the financial market. The average of the CES is shown according to the industry groups. The forecasting periods were divided into eight stages, namely, half year per period, shown in Table 5. Comparing the rankings of the CES score across the eight stages for both methods, it can be seen that the rankings at the top 10 listed companies are about the same. This is similar to predictions made by the research of Banulescu and Dumitrescu [3]. During COVID-19, from stage 5 to stage 8, the absolute CES values of top financial institutions showed an upward trend, indicating that the epidemic increased the contribution of listed companies in the US financial industry to the systemic financial risk of the financial market in general.

Table 5. Top 10 US financial firms ranks by CES before and during COVID-19.

Before COVID-19				**Copula–GARCH**			
Stage 1		**Stage 2**		**Stage 3**		**Stage 4**	
WFC	0.00350	WFC	0.00358	WFC	0.00253	JPM	0.00352
JPM	0.00223	JPM	0.00274	JPM	0.00251	BAC	0.00256
BAC	0.00179	BAC	0.00193	BAC	0.00176	WFC	0.00180
C	0.00107	C	0.00138	C	0.00099	C	0.00052
MS	0.00017	GS	0.00019	GS	0.00015	MS	0.00014
GS	0.00016	MS	0.00016	MS	0.00015	GS	0.00014
USB	0.00014	USB	0.00015	MET	0.00011	AIG	0.00008
AXP	0.00012	AXP	0.00014	AXP	0.00009	SCHW	0.00007
BLK	0.00009	BLK	0.00012	SCHW	0.00008	USB	0.00006
COF	0.00009	SCHW	0.00010	BLK	0.00008	AXP	0.00005
Before COVID-19				**DCC–GARCH**			
Stage 1		**Stage 2**		**Stage 3**		**Stage 4**	
WFC	0.00589	WFC	0.00961	WFC	0.00386	JPM	0.00363
AIG	0.00258	JPM	0.00192	JPM	0.00336	WFC	0.00333
BAC	0.00255	BAC	0.00165	BAC	0.00321	BAC	0.00320
JPM	0.00173	C	0.00045	C	0.00114	C	0.00089
C	0.00089	AIG	0.00014	MS	0.00025	MS	0.00018
MS	0.00015	USB	0.00013	GS	0.00013	GS	0.00014
GS	0.00010	MS	0.00007	USB	0.00010	USB	0.00008
USB	0.00008	GS	0.00006	BLK	0.00009	BLK	0.00007
AXP	0.00006	BLK	0.00005	AIG	0.00008	SCHW	0.00007
HIG	0.00006	AXP	0.00003	SCHW	0.00006	AXP	0.00006
During COVID-19				**Copula–GARCH**			
Stage 5		**Stage 6**		**Stage 7**		**Stage 8**	
JPM	0.01820	JPM	0.00774	JPM	0.00814	JPM	0.00421
BAC	0.00485	BAC	0.00297	BAC	0.00243	BAC	0.00306
WFC	0.00115	C	0.00076	WFC	0.00070	WFC	0.00097
C	0.00111	WFC	0.00070	C	0.00031	MS	0.00044
AXP	0.00046	MS	0.00038	MS	0.00027	SCHW	0.00037
MS	0.00037	SCHW	0.00028	SCHW	0.00020	AXP	0.00033
SCHW	0.00034	AXP	0.00026	AXP	0.00013	C	0.00023
BLK	0.00033	BLK	0.00022	BLK	0.00011	GS	0.00017
GS	0.00023	GS	0.00021	GS	0.00008	BLK	0.00015
SPGI	0.00021	SPGI	0.00021	SPGI	0.00008	SPGI	0.00011
During COVID-19				**DCC–GARCH**			
Stage 5		**Stage 6**		**Stage 7**		**Stage 8**	
JPM	0.00511	JPM	0.00685	JPM	0.00678	JPM	0.00824
BAC	0.00204	AXP	0.00174	AIG	0.00484	AXP	0.00624
C	0.00060	BAC	0.00170	AXP	0.00417	BAC	0.00187
WFC	0.00053	C	0.00050	BAC	0.00141	HIG	0.00057
AXP	0.00027	WFC	0.00026	WFC	0.00054	WFC	0.00041
MS	0.00022	MS	0.00020	C	0.00029	C	0.00010
SCHW	0.00022	SPGI	0.00017	SPGI	0.00011	MS	0.00010
BLK	0.00017	SCHW	0.00013	MS	0.00007	SPGI	0.00007
SPGI	0.00017	BLK	0.00012	GS	0.00004	AIG	0.00006
GS	0.00013	GS	0.00008	SCHW	0.00004	SCHW	0.00006

According to the values of CES% in the US financial market, Table 6 displays the top 10 largest contributors of systemic financial risk for eight stages. To sum up, the top 10 contributors resulted in a risk contribution of over 90%. By analyzing the identification of the top 10 risk contributors for all eight stages, both methods recognized roughly the same financial firms. In particular, in the fifth stage of the epidemic outbreak, both the copula–GARCH and the DCC–GJR–GARCH identified exactly the same top 10 institutions. Notably, the predictions of the linear dependency model showed higher values in terms of CES% than the nonlinear model. However, during the out-break period, the Copula–GARCH predicted risk that is larger than the other.

Table 6. Top 10 US financial firms ranks by CES% before and during COVID-19.

Before COVID-19				**Copula–GARCH**			
Stage 1		**Stage 2**		**Stage 3**		**Stage 4**	
WFC	31.56	WFC	31.51	WFC	27.93	JPM	37.35
JPM	22.44	JPM	24.02	JPM	26.76	BAC	26.99
BAC	18.48	BAC	17.04	BAC	19.14	WFC	19.46
C	11.04	C	12.35	C	10.45	C	5.80
MS	1.74	GS	1.71	GS	1.71	MS	1.59
GS	1.71	MS	1.47	MS	1.63	GS	1.51
USB	1.30	USB	1.29	MET	1.24	AIG	0.88
AXP	1.27	AXP	1.17	AXP	1.01	SCHW	0.79
COF	1.05	BLK	1.07	BLK	0.92	USB	0.65
BLK	1.01	SCHW	0.90	SCHW	0.91	AXP	0.55
Sum	91.6	Sum	92.53	Sum	91.7	Sum	95.57
Before COVID-19				**DCC–GARCH**			
Stage 1		**Stage 2**		**Stage 3**		**Stage 4**	
WFC	42.02	WFC	52.49	WFC	29.86	JPM	30.35
BAC	19.62	JPM	18.28	JPM	26.32	WFC	26.23
JPM	14.02	BAC	15.66	BAC	24.98	BAC	25.79
AIG	9.61	C	5.06	C	8.98	C	7.78
C	7.12	AIG	1.30	MS	2.00	MS	1.58
MS	1.25	USB	1.23	GS	1.01	GS	1.22
GS	0.86	MS	0.86	USB	0.76	USB	0.68
USB	0.63	GS	0.72	BLK	0.70	BLK	0.62
AXP	0.51	BLK	0.61	AIG	0.61	SCHW	0.60
BLK	0.45	AXP	0.38	SCHW	0.48	AXP	0.50
Sum	96.09	Sum	96.59	Sum	95.7	Sum	95.35
During COVID-19				**Copula–GARCH**			
Stage 5		**Stage 6**		**Stage 7**		**Stage 8**	
JPM	55.09	JPM	48.14	JPM	49.69	JPM	38.74
BAC	21.32	BAC	21.01	BAC	23.87	BAC	28.18
WFC	5.14	C	5.10	WFC	6.72	WFC	9.24
C	4.88	WFC	4.91	C	3.11	MS	4.20
AXP	1.78	MS	2.76	SCHW	2.91	SCHW	3.47
MS	1.52	SCHW	1.94	MS	2.86	AXP	2.94
SCHW	1.42	AXP	1.92	AXP	1.38	C	2.16
BLK	1.00	BLK	1.61	GS	1.29	GS	1.63
GS	0.81	SPGI	1.48	BLK	1.27	BLK	1.42
SPGI	0.81	GS	1.40	PNC	0.65	SPGI	1.02
Sum	93.77	Sum	90.27	Sum	93.75	Sum	93.00
During COVID-19				**DCC–GARCH**			
Stage 5		**Stage 6**		**Stage 7**		**Stage 8**	
JPM	48.23	JPM	54.12	JPM	50.71	JPM	45.31
BAC	20.36	BAC	17.48	AXP	15.47	AXP	18.98
C	5.95	AXP	5.67	BAC	14.31	BAC	17.91
WFC	5.41	C	5.09	WFC	5.29	WFC	4.47
AXP	2.63	WFC	2.80	C	3.26	HIG	2.46
SCHW	2.25	MS	2.32	AIG	2.70	MS	1.75
MS	2.23	SPGI	1.91	MS	1.40	C	1.56
BLK	1.68	SCHW	1.60	SPGI	1.23	SCHW	1.29
SPGI	1.68	BLK	1.45	SCHW	1.06	SPGI	0.83
GS	1.29	GS	0.96	GS	0.81	GS	0.79
Sum	91.71	Sum	93.40	Sum	96.24	Sum	95.35

Two discontinued lines in Figure 2 represent the total CES for the two scenarios of pre-COVID-19 and during-COVID-19 with blue and orange, respectively. Figure 2 clearly demonstrates that there does exist a high systemic risk at the beginning of the COVID-19 pandemic. This prediction is roughly accurate in terms of forecasting trends and extreme loss events. On 11 February 2020, the World Health Organization officially named the new coronavirus COVID-19. Since then, with CES in 2020, two key facts of systemic risk have been captured by comparing SP500. First, the US stock market has been falling since 20 February and did not reach a trough until 23 March 2020. At the same time, SP500 decreased by 33.9%. Second, on 11 June, the United States reported a total of 2 million cases and 112.9 thousand deaths in terms of the COVID-19, and then the SP500 declined by 8.89% at the same day. The features of overall systemic risk in the US financial market have been well captured by the CES.

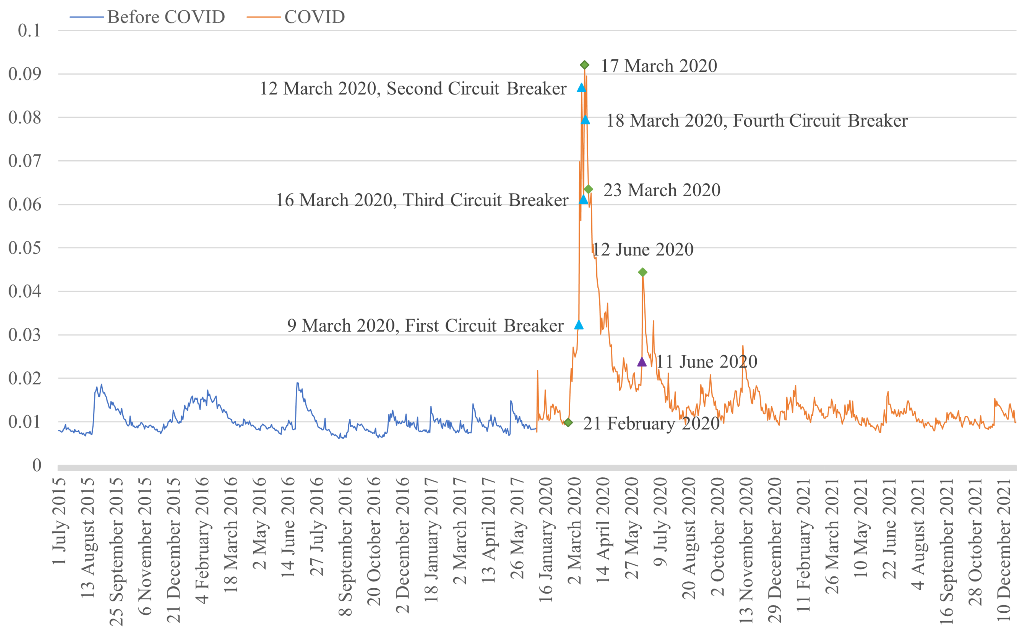

Figure 2. CES before and during COVID-19 epidemic in US financial market. The blue line represents the CES before the outbreak of the COVID-19 pandemic, and the orange line represents the CES after the outbreak.

Referring to Figure 3, the predicted systemic risk, represented by CES% contribution for the four groups, was compared and some facts were revealed as follows: First, for two periods, Depositories contributed the largest share of systemic risk with over 84%. Broker–Dealers, Insurances, and Others contributed in descending order with CES% less than 7% in sum. Second, after the COVID-19 outbreak, the percentage contribution to systemic risk from Depositories decreased by 4.7%, Insurances decreased by 0.8%, Broker–Dealers increased by 2.2%, and Others increased by 3.3%.

By evaluating the monthly average CES% of the four groups of financial institutions (see Figure 4), we can see that there is a opposite pattern between Depositories and other non-bank financial institutions both before and during the epidemic. However, since the outbreak of the COVID-19 epidemic, the monthly average CES percentage variation of four groups has changed significantly. Comparing pre-COVID-19 and post-COVID-19 periods, the range of the Depositories has increased from 7.4% to 18.4%, the insurance has slightly decreased from 4.4% to 3.4%, the Broker–Dealers has increased from 2.5% to 9.9%, and the Others rose from 3.4% to 9.5%. In March 2020, which was the period most affected by the epidemic, savings financial institutions reached a very low point, while other non-bank financial institutions reached a peak, which is also the maximum of insurance and other groups. However, the proportion of risk contribution of Broker–Dealers continued to rise during the epidemic, and only reached the maximum value of the forecast period in October 2021.

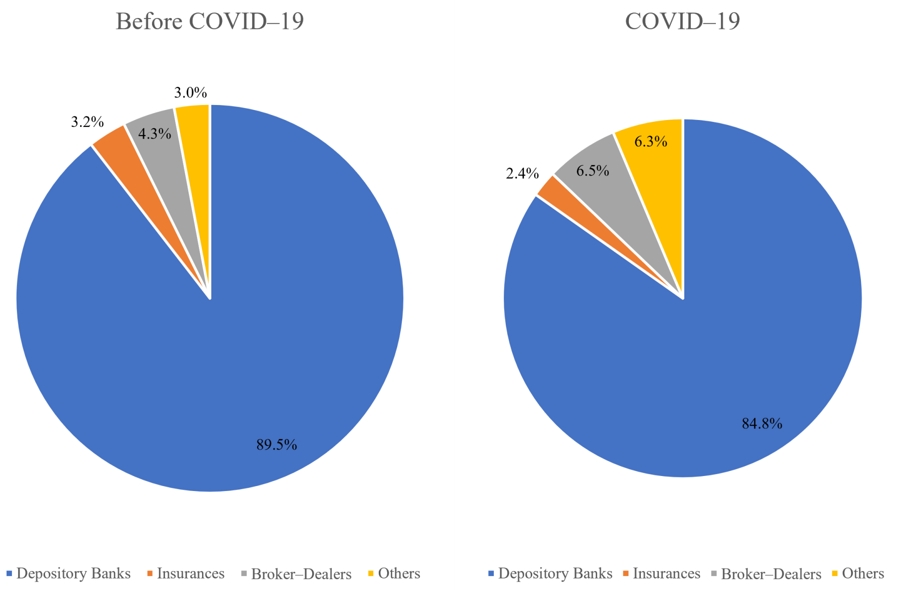

Figure 3. Value of CES% contribution for four groups of financial institutions before and during COVID-19.

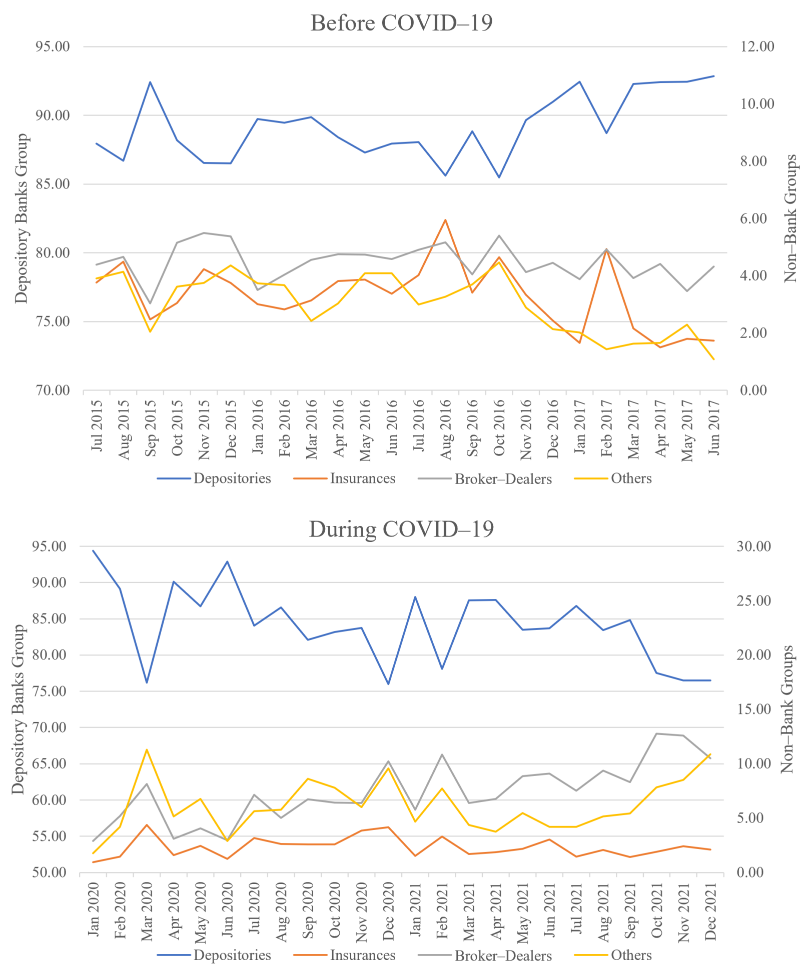

Figure 4. Monthly average CES% for four financial groups.

5. Conclusions

The US financial market was very risky at the beginning of the COVID-19 pandemic, which has attracted the attention of many scholars and researchers. This paper used the copula–GJR–GARCH models to reveal the dependency structures between 60 US financial firms and the US financial market and their leverage effects. On this basis, the systemic financial risk in the US was predicted by using CES and was compared two periods: before the COVID-19 outbreak and during the COVID-19 epidemic.

The empirical results showed that the copula–based model performed better than the DCC–GARCH in predicting the systemic risk intuitively, and that these results can be explained by two explanations. The copula model accounts for the tail correlation and performed better estimation and forecasting in the context of an extreme market decline. It demonstrated the advantages of rank correlation of a nonlinear dependency structure for the copula-based model over the linear correlation in terms of the DCC–GJR–GARCH model. The rank correlation analysis provided solid evidence that Depositories has the greatest impact on the financial market. Depositories also exhibit the characteristics of tail dependency, suggesting a similar pattern for upswing or downswing situations. It is worth noting that MS, a broker–dealer company, had a high correlation to the financial market with asymmetric tail. The large lower tail explained that broker–dealer firm correlation to the market appeared to increase when the market declined. Overall, these companies have a high market relevance due to their large market share. Most of these companies have tail correlation values greater than 0.5, which explains why the top 10 publicly traded companies are closely correlated with bull and bear markets.

The systemic risk analysis showed that the risk contributions of the top institutions in the eight stages are basically similar. The features can be captured by both models based on assumptions of a linear dependency and a nonlinear dependency. It shows that the US financial industry has the market characteristics of the strong stay strong, which is consistent before and after the epidemic.

The empirical results show that during COVID-19, the overall systemic risk of the US financial institutions increased. The similar top 10 SIFIs with the highest assets under two scenarios and eight stages were found with slightly different rankings. The largest corporations continue to play the most significant role in the industry and have the determining impact on financial risk, contributing most of the whole. It is noticeable that broker–dealers' sensitive reaction to the market downturn led to a sharp increase in their market capitalization in the early phase of the COVID-19 outbreak. Reverse growth characteristics made Broker–Dealers the largest contributor to risk after the epidemic intensified. Methodologically, the linear dependency assumption overestimated pre-epidemic risk and underestimated post-epidemic risk, showing that the nonlinear dependence structure has obvious risks in measuring systemic risk.

The systemic risk analyzed by CES in the US financial markets has risen sharply since late February 2020, and the CES approach fully captures the four US stock market crashes over the period. We found that the last circuit breaker tripped when systemic risk was at its peak. After that, the CES began to decline continuously, showing that the impact of externalities on the financial market has been gradually eliminated, and the corresponding countermeasures and safeguards of the US financial market have played a corresponding role. This phenomenon also demonstrates the ability of the CES method to analyze overall risk when a major risk materializes.

Depositories contributed the greatest systemic risk to US financial industry of the four financial categories. However, they were the least vulnerable group to financial market risks. Instead, Broker–Dealers were the most vulnerable group when faced with an enormous financial risk shock. While the risk of the financial markets increases, the share of Depositories in the risk contribution shrinks, as do the insurance companies. In contrast, the share of systemic risk from broker–dealers and other financial institutions increased during COVID-19.

The contribution of Depositories and Insurances to financial risk decreased during the epidemic, which does not lead to the conclusion that their risk has decreased. In contrast, the COVID-19 outbreak has led to an increase in systemic risk for all types of financial institutions, among which Broker–Dealers and Others have made a greater contribution. This conclusion is supported by a monthly average CES%. We found that the risk contribution of Depositories decreased as the risk contribution of the other three types of institutions increased. This contrasting feature is evidenced by Bank of America playing some role in hedging against changes in systemic risk during the epidemic.

The policy recommendations of this study suggest that fiscal policy supervisors should introduce macroprudential guidance of SIFIs with high systemic risk at the early stage when external risks begin to spill over into financial markets and emerge as extreme risks. We should pay particular attention to Broker–Dealers and Others in order to improve the financial stability of the US financial market.

There are some flaws in the study as well. With the development of copulas, vine copulas and factor copulas have been employed to fit high dimensional data [8,38]. Because this study has over 60 variables, we may use factor copulas to fit the data. Although the forecasting of systemic risk in this study is reasonable intuitively, a statistical test might strengthen our conclusions.

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Abbreviations

The following abbreviations are used in this manuscript:

MES	Marginal Expected Shortfall
CES	Component Expected Shortfall
CES%	Percent Change of Component
Depositories	Depository banks
Insurances	Insurance institutions
Broker–Dealers	Brokers– and Dealers
Others	Other financial institutions

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