The Impact of Disaster Events on Investments - Contagion Channels Perspective

OCTOBER | 2022

Catastrophe and Climate

The Impact of Disaster Events on Investments

Contagion Channels Perspective

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Executive Summary

Weather and climate disasters occur every day somewhere in the world. These extreme weather and climate disasters claim tens of thousands of lives each year and have significant economic effects on the areas impacted. One critical characteristic of a powerful natural disaster is that it adversely affects large parts of the domestic economic sectors, and its negative impact may spread contagiously in the financial markets as a threat to financial stability.

As a financial systemic risk, financial contagion has attracted substantial attention from investors, regulators, and the public. However, the investment contagion caused by disaster events is convoluted, and the contagious nature of the impact of large-scale disaster events on investments is not well studied yet in the literature. Due to the different nature and geographic locations of the natural disasters, they may have different direct and indirect spillover impacts on different asset classes and investment sectors. However, the natural disaster-driven financial contagion has not been fully investigated in the literature. This research aims to fill the gap.

The focus of this research is to study the extent to which investment sectors have been contagiously affected by major disasters. To pursue this task, we first investigate the existence of financial contagion from cross-sector perspective on major types of natural disasters. Financial contagion is mostly defined as a significant increase in cross-market linkages after a shock (Forbes and Rigobon, 2002). Following the recent technological advancement (Wang et al., 2021), this research proposes to use the dynamic copula-EVT (extreme value theory) model that incorporates both the tail behavior and the complex dependence structure between financial markets to examine the existence of disaster-driven financial contagion cross-sector of the US stock market.

We find evidence that the financial contagion caused by natural disaster events is convoluted and heterogeneous under different types of natural disaster events. More specifically, our results confirm the existence of financial contagion during these types of disaster events, and the West Nile fever and oil spill events are the easiest to driven financial contagion, while the drought event has the least influence on financial market. Moreover, the automobile and wholesale sectors are the most affected by disasters and are found to be highly risky.

We further identify the main contagion transmission channels during the natural disaster periods. While there is a sizable literature focusing on contagion transmission channels during financial crises, the implications from the previous literature may not be directly applicable to natural disaster-driven financial contagion. This research sheds light on this topic and provides new evidence that a majority of financial contagion driven by natural disasters is spread through portfolio rebalancing.

To limit the contagion associated with wealth constraints, international financial risk managers could provide timely support to the struggling financial institutions so as to reduce investors' perceived risk. Also, policymakers and experts may reevaluate the global financial system regulation and take appropriate reactions to limit recessions. Our findings shed light on the transmission mechanism of disaster events on the sectors.

Section 1: Introduction on Natural Disaster-Driven Financial Contagion

Weather and climate disasters occur every day somewhere in the world. These extreme weather and climate disasters claim tens of thousands of lives each year and have significant economic effects on the areas impacted. According to the National Oceanic and Atmospheric Administration, from 1980-2021, there have been 300 extreme weather catastrophic events with losses exceeding $2,086 billion across the United States with total deaths of 15,030 people.[1] Globally, over 475,000 people perished in extreme weather and climate catastrophes over 20 years during the 2000 to 2020 period (United Nation 2021)[2]. The US faced unprecedented natural disasters in 2021 with record fires on the West Coast, frequent hurricanes in the Southeast, and the deadliest late-season tornado outbreaks (of December 10-11, 2021) ever recorded in the United States ravaged parts of the South and Midwest.

The World Meteorological Organization (WMO) 2021 annual report shows evidence of an increasing number of extreme climate events considered as systemic risks.[3] Scientists are pointing to increasing signs of extreme climate and its bigger and more damaging impacts on the planet and on people's lives. The increased risk of extreme weather catastrophe such as prolonged droughts, recurrent heatwaves, record rainfall and damaging floods often exerts a disproportionate impact on the low and middle-income countries which could damage a large part of their production capacity. As Table 1 shows, the average number of annual billion-dollar disasters has grown from 2.9 per year in the 1980s to 12.2 per year in the 2010s and was 22 in 2020 according to National Centers for Environmental Information (NCEI).

Table 1

SELECT TIME PERIOD COMPARISONS OF UNITED STATES BILLION-DOLLAR DISASTER STATISTICS (CPI-ADJUSTED)

Time Period	Billion-Dollar Disasters	Events/Year	Cost	Percent of Total Cost	Cost/Year	Deaths	Deaths/Year
1980s (1980-1989)	29	2.9	$187.2B	9.00%	$18.7B	2,870	287
1990s (1990-1999)	53	5.3	$288.6B	13.80%	$28.9B	3,045	305
2000s (2000-2009)	63	6.3	$547.0B	26.20%	$54.7B	3,091	309
2010s (2010-2019)	123	12.3	$858.4B	41.10%	$85.8B	5,224	522
Last Year (2020)	22	22	$100.2B	4.80%	$100.2B	262	262
All Years (1980-2021)*	308	7.3	$2,086.2B‡	100.0%‡	$49.7B‡	15,030	358

NOTE: Statistics valid as of October 8, 2021

Global or regional climate risk pools could potentially help enhance climate resilience and prevent fiscal shocks in vulnerable countries. Regional and national efforts to step up climate risk pools have encompassed a host of initiatives. For example, the World Bank's Global Index Insurance Facility supports the development of index-based disaster insurance for farmers. Yet the high uncertainty about future extreme events, the dynamics of assessing the increasingly unpredictable nature of weather patterns as well as the covariance among systemic risks pose important hurdles that must be overcome.

1 https://www.ncdc.noaa.gov/billions/summary-stats
2 https://www.scientificamerican.com/article/climate-fueled-disasters-killed-475-000-people-over-20-years/
3 https://public.wmo.int/en/media/news/state-of-global-climate-observing-system-2021

Natural disasters could inflict serious damages on people's lives, property, and economy. Powerful disasters such as earthquakes, hurricanes and wildfires may also cause heavy damage to the financial markets of individual investments and may even spillover to the broad financial markets (regions) as evident from the US Hurricane Katrina of 2005, the Japan earthquake and tsunami of 2011, and the Australia wildfires of 2020. The rapid outbreak of COVID-19 and the subsequent rapid spread of the financial crisis in 2020 highlight the similarity between the virus spread in population and the financial crisis spread across different asset classes or across countries. Not surprisingly, "contagion"—an epidemiological term—has been widely adopted to describe the nature of spillover impact of large-scale events on investments and financial markets.

The systemic extreme weather and climate risk pooling can build on experiences of a number of existing catastrophe risk pools for natural disasters. For instance, the Caribbean Catastrophe Risk Insurance Facility (CCRIF) is the first multi-country risk pool in the world. The African Risk Capacity (ARC) is created as a specialized agency of the African Union. The Pacific Catastrophe Risk Insurance pilot was designed by the World Bank, which was considered not to meet the optimistic expectations of advocates including development partners (Dornan and Cain, 2014). The Shenzhen Social Insurance Program is China's large-scale experiment with a nationally funded city-wide model of disaster insurance.

As a financial systemic risk, financial contagion has attracted substantial attention from investors, regulators, and the public. However, the investment contagion caused by disaster events is convoluted, and the contagious nature of the impact of large-scale disaster events on investments is not well studied yet in the literature. Due to the different natures and geographic locations of the natural disasters, they may have different direct and indirect spillover impacts on different asset classes and investment sectors.

The focus of this research is to study the extent to which different asset classes and investment sectors have been contagiously affected by major disasters. To understand the disaster-driven financial contagion, it is critical to develop accurate techniques to detect and measure financial contagion. The nature of financial contagion requires the exploration of conditional extreme dependence rather than the widely used correlation between different markets. In this research, we propose to use the copula-based model to study the disaster-driven financial contagion. Most importantly, we propose to use the corner tail dependence which captures the circumstances when different markets move in the same direction at the extreme dependence as the measure of disaster contagion.

When the disaster-driven financial contagion exists, the correlation between the sectors would increase significantly during crisis periods compared to tranquil periods. In this work, the lower tail dependence achieved by the copula-based model is proposed as the measures of disaster-driven financial contagion to incorporate the complex tail dependence including non-linearity, asymmetry, and dynamic pattern. We also use both the lower tail dependence and upper tail dependence to measure the asymmetric reactions to market boom and market crash and determine the channels of the disaster-driven financial contagion.

Section 2: Literature Review

Financial contagion is defined as a significant increase in cross-market correlation after extreme shocks (Forbes and Rigobon, 2002). Using this definition, the vector autoregression approach (Dungey et al., 2020) and the multivariate generalized autoregressive conditional heteroscedasticity (GARCH) family model (Niţoi and Pochea, 2019) have been employed to test the existence of financial contagion in the earlier literature. However, correlation measures mask the complex and nonlinear dependence between markets and fail to reveal the characteristics of tail dependence (Ming et al., 2022). To overcome this, a strand of literature focuses on financial contagion based on dependence instead of correlation. In particular, Wang et al. (2021) construct a dynamic copula-EVT model to detect the existence of financial contagion. The dynamic copula-EVT model incorporates both the tail behavior and the complex dependence structure between financial markets. Studies have mostly discussed the contagion effect among markets during financial crises, such as the 1997 Asian financial crisis, the 2008 global financial crisis, the 2011 European debt crisis, and the 2020 COVID-19 crisis (Boyer et al., 2006; Bekaert et al., 2014; Wang et al., 2021).

Limited attention is dedicated to disaster events (such as earthquake, storm, flood, and transport accident) on financial contagion. Previous literature shows that weather and climate catastrophic risks induce extreme tail risks and systemic correlations in losses and thus may challenge the standard insurability conditions. Kunreuther et al. (1995) and Cummins and Trainar (2009) show that actuaries tend to charge much higher premiums if risks are not well specified or correlated. As a result, catastrophic insurances often have substantial high risk premium loadings (Froot, 2001; Hochrainer, 2006). Linnerooth-Bayer and Mechler (2007) indicate that it is often too costly to insure against very extreme risks occurring less frequently than every 500 years. The existence of systemic weather risk has been argued as the main reason for the failure of private crop insurance markets (Miranda and Glauber, 1997; Duncan and Myers, 2000).

On the other hand, by means of spatial statistics approach, Goodwin (2001) and Wang and Zhang (2003) suggest that only a moderate premium loading is necessary for covering the systemic yield risk if the risk pool is large enough. Okhrin et al. (2013) explore the possibility of spatial diversification of weather risk for agricultural production regions in China and find that the spatial diversification effect depends on the type of weather index and the strike level of the insurance. Xu et al. (2010) showed similar results on systemic weather risks for the German market. Using the Japanese 311 earthquake in 2011 as a case study, Huang et al. (2018) provide evidence of spatial contagion for neighboring countries exporting to Taiwan. Li et al. (2021) shows that the Japan Kumamoto earthquakes in 2016 caused financial contagion effect and the contagion effect overweighs the competitive effect. More recently, a spate of literature focus on the COVID-19 pandemic and analyze its impact on economy and financial market (e.g., Duan et al., 2021; Foley et al., 2021; Huber et al., 2021; John and Li, 2021). For instance, according to Wang et al. (2021), the COVID-19 pandemic leads the financial contagion phenomenon between oil and stock markets and the magnitude of financial contagion exceeds that during the 2008 financial crisis.

Provided that contagion appears to prevail on many markets, a natural stream of research is the analysis of the channels underlying the shock transmissions across markets. This topic is of importance, e.g., for investors seeking to hedge against market downturns and policymakers who aim to limit the consequences of such stressful periods. An in-depth understanding of the mechanisms driving financial contagion will contribute to more appropriate decisions and provide for more targeted interventions. To the best of our knowledge, no research has been carried out to examine the channels of disaster-driven financial contagion. We believe that it is important to fill such a gap given the role played by the disaster events and the importance of this factor on the economy.

The literature has recognized at least three possible channels of financial contagion, i.e., financial linkages, trade links, and investor behavior (Kaminsky et al., 2003). In the wake of the growing behavioral economics literature that points to the role played by investor attention and investor sentiment in the price formation and return co-movements (Ben-Rephael et al., 2017; Gao et al., 2020; Gu and Kurov, 2020; Hsieh et al., 2020), we also evaluate the importance of a behavioral dimension. That is, our focus is on the testing of the investor behavior hypothesis in explaining the linkages between disasters and financial contagion in the US. As a consequence of the models developed by Kyle and Xiong (2001), the financial contagion of behavior dimension is spread through the wealth effect when investors suffering loss struggle to meet their liquidity constraints through fire sale. Yet, this theory implies asymmetric reactions to both market boom and market crash. An alternative investor behavior-induced financial contagion is through the portfolio rebalancing channel suggested by the rational expectations model of Kodres and Pritsker (2002).

Section 3: Natural Disaster-Driven Financial Contagious Detection Model

3.1. THE COPULA-EVT MODEL

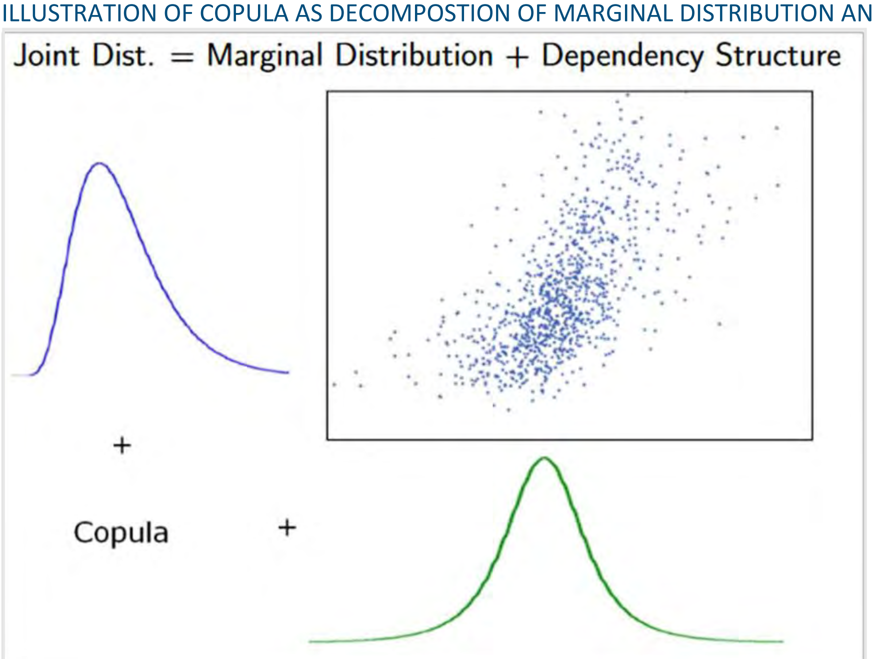
The copula is a function that describes various patterns of dependence structures and has been widely used to measure financial contagion. The essence of copula is that a joint distribution of random variables can be expressed as a function of the marginal distributions. To make this notion precise, let's review one of the most essential mathematical results in the copulas theorem: the Sklar theorem in 1959. According to Sklar's (1959) theorem, let Z_1 and Z_2 denote two random variables with bivariate joint distribution function F_{Z_1,Z_2} and two continuous marginal distribution functions F_1 and F_2, then there is a unique copula $C:[0,1]^2 \to [0,1]$ such that

$$F_{Z_1,Z_2}(z_1, z_2) = C(F_1(z_1), F_2(z_2)). \quad (1)$$

Essentially, Sklar's Theorem says, any joint distribution can be written in copula form, and the use of copula allows the separation of the marginal distribution from the dependence structure. Therefore, the joint distribution can be constructed from two independent components: the copula and the information of the marginal distributions. Copula fully captures the dependence relationship in a multi-variate distribution. The use of the copula allows the separation of the marginal distribution from the dependence structure. Therefore, the joint distribution can be constructed from two independent components: the copula and the information of the marginal distributions. Figure 1 illustrates the intuition of copula as the decomposition of marginal distribution and the dependence structure of the joint distributions. The scatter plot of the two uncertainties shows how one uncertainty is covarying with another uncertainty. If we extract out the marginal distribution of each uncertainty, whatever is left is the complete dependence structure between them, which is fully captured by a copula.

Figure 1

ILLUSTRATION OF COPULA AS DECOMPOSTION OF MARGINAL DISTRIBUTION AND DEPENDENCY STRUCTURE

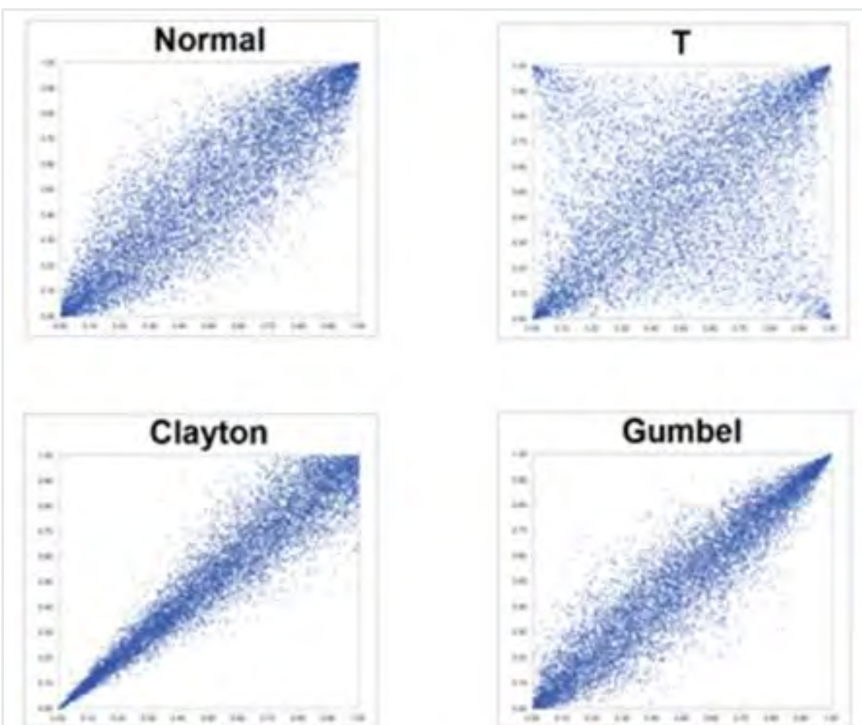


There are many different types of copulas to describe different types of dependence relationships. The dependence relationship is commonly measured with linear correlations. There are more complex dependency structures. For instance, in some practical applications, there may be a stronger dependence between big losses, such as stock price movement when the market crashes, or between big gains with a market melt up. Such asymmetry of the dependence structure is called tail dependence.

The elliptical copulas and Archimedean copulas are among the most popular copula families. The elliptical copulas and the Archimedean copulas differ significantly in modeling the tail dependency of distributions. The normal copula is the copula that underlies the multivariate normal distribution. It shares the same dependency structure with the multivariate normal distribution. The normal copula has upper and lower tail dependencies equal to zero. The t-copula presents symmetric and positive upper and lower tail dependence, which indicates a tendency for the t-copula to generate joint extreme events.

Archimedean copulas model upper tail dependency, lower tail dependency, or both, so that they provide additional flexibility to describe the behavior of tail dependency in realistic situations. Clayton and Gumbel copulas are among the most popular Archimedean copulas. The Clayton copula exhibits asymmetric lower tail dependence and is best suited for applications in which two outcomes are likely to experience low values together. The Gumbel copula exhibits asymmetric upper tail dependence and is best suited for applications in which two outcomes are likely to experience high values together such as the performance of stock returns during a market jump. Figure 2 illustrates the tail dependence of the most common copulas including normal copula, t copula, clayton copula and gumbel copula.

Figure 2
ILLUSTRATION OF TAIL DEPENDENCE OF DIFFERENT COPULAS



We can also quantify the tail dependence. Tail dependency measures the probability that extreme events happen jointly. Upper tail dependence exists when there is a probability that positive extreme events happen jointly. Lower tail dependence is defined symmetrically. The tail dependency measure depends only on the copula and not on the marginal distributions. One advantage of the copula models is that they can mathematically describe the tail dependence, which measures the probability that two variables exhibit extremely small values or extremely large values together. The lower tail dependence coefficient (λ^L) and upper tail dependence coefficient (λ^U) are correspondingly defined as

$$\lambda^L = \lim_{\varepsilon\to 0} P\left[Z_1 < F_1^{-1}(\varepsilon) \mid Z_2 < F_2^{-1}(\varepsilon) \right] = \lim_{\varepsilon\to 0} \frac{C(\varepsilon,\varepsilon)}{\varepsilon}, \quad (2)$$

$$\lambda^U = \lim_{\varepsilon\to 1} P\left[Z_1 \geq F_1^{-1}(\varepsilon) \mid Z_2 \geq F_2^{-1}(\varepsilon) \right] = \lim_{\varepsilon\to 1} \frac{1\text{-}2\varepsilon + C(\varepsilon,\varepsilon)}{1\text{-}\varepsilon}, \quad (3)$$

where F_1^{-1} and F_2^{-1} are two marginal quantile functions and $\lambda^L, \lambda^U \in [0,1]$. λ^L being 0 and positive implies independence and dependence of Z_1 and Z_2 in the lower tail, respectively. Larger λ^L suggests stronger dependence. A similar statement holds for the dependence in the upper tail based on the value of λ^U .

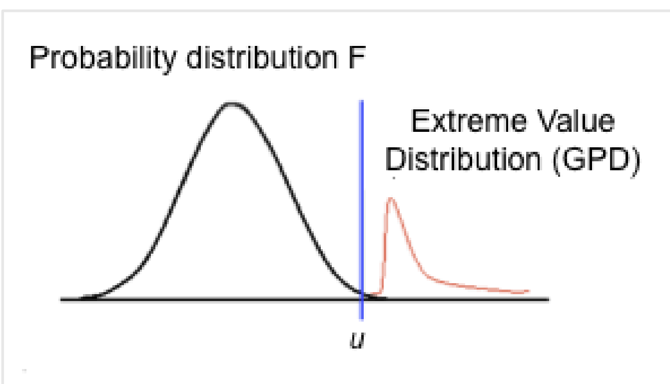
3.2. MARGINAL DISTRIBUTION MODELING

The use of copula takes care of the extreme tail dependences. We also need to take care of the extreme tail in the marginal distributions. The GARCH-type models are usually adopted to construct marginal distributions (Fenech and Vosgha, 2019; Ji et al., 2018). One drawback of the GARCH-type models is that they perform poorly in the tail distribution modeling (Koliai, 2016; Sahamkhadam et al., 2018), while the tail behavior is essential in measuring financial contagion.

To overcome the disadvantage of GARCH-type models in tail distribution modeling (Koliai, 2016), we model the marginal distribution with EVT in combination with the GARCH-type model. More specifically, the Generalized Pareto Distribution (GPD) is used to specify the extreme values of the standardized residuals.

Figure 3

ILLUSTRATION OF EXTREME VALUE THEORY



The standardized residuals are from the AR(1)-GJR(1,1) model with skewed-t distribution (Fomby et al., 2012; Meine et al., 2016). The default GJR(P,Q) model is of the form $\varepsilon_t = \sigma_t z_t$, with Gaussian innovation distribution and $\sigma_t^2 = \kappa + \sum_{i=1}^{P} \gamma\ \sigma_{t-i}^2 + \sum_{j=1}^{Q} \alpha_j \varepsilon_{t-j}^2 + \sum_{j=1}^{Q} \xi_j\, I\left[\varepsilon_{t-j} < 0\right] \varepsilon_{t-j}^2$. The indicator function $I\left[\varepsilon_{t-j} < 0\right]$ equals 1 if $\varepsilon_{t-j} < 0$ and 0 otherwise. The default model has no mean offset, and the lagged variances and squared innovations are at consecutive lags.[4]

To do so, we use the peaks over threshold method according to which, the distribution of excess returns (i.e., return minus extreme threshold) follows the GPD. Following Koliai (2016), we use the 10th (lower tail) and 90th (upper tail) percentiles of the standardized residual series as the extreme thresholds and model the tails of the marginal distributions beyond the extreme thresholds with GPD. The standardized residuals falling between the extreme thresholds are modeled using the empirical cumulative distribution function. The marginal distribution is thus given as follows

$$F_i(z_i) = \begin{cases} \frac{N_{u_L}}{N}\left(1-\xi_L\frac{\hat{z}_i-u_L}{\beta_L}\right)^{-1/\xi_L}, & \hat{z}_i < u_L, \\ \varphi(z_i), & u_L \le \hat{z}_i \le u_U, \\ 1-\frac{N_{u_U}}{T}\left(1+\xi_U\frac{\hat{z}_i-u_U}{\beta_U}\right)^{-1/\xi_U}, & \hat{z}_i > u_U, \end{cases} \tag{4}$$

where z is the standardized residual series for stock index i, $\mu_{i,L}$ and $\mu_{i,U}$ are the lower and upper-tail thresholds, respectively; $N_{\mu_{i,L}}$ ($N_{\mu_{i,U}}$) is the number of observations below (above) the threshold $\mu_{i,L}$ $(\mu_{i,U})$; $\beta_{i,L}$ and $\xi_{i,L}$ $(\beta_{i,U}, \xi_{i,U})$ are the scale parameter and the shape parameter of the GPD on the lower (upper) tail, respectively; N is the number of observations; and φ is the empirical cumulative distribution function about z_i.

Section 4: Disaster-Driven Contagion Network

4.1. DISASTER-DRIVEN CONTAGION NETWORK CONSTRUCTION

A complex network is a collection of nodes linked by edges, and it is always employed to show the complex links between financial markets (Demange, 2018b; Gen¸cay et al., 2020; Schuldenzucker et al., 2020b; Huang et al., 2021; Cheng et al., 2022; Hurn et al., 2022). In this study, we propose a new disaster-driven financial contagion network based on the dynamic mixture copula-EVT model to investigate the characteristics of disaster-driven financial contagion. In our disaster-driven financial contagion network, the nodes are considered as 26 stock markets, and the edges between nodes represent the existence of disaster-driven financial contagion between the corresponding stock markets. The network structure of the edges can also be expressed as an asymmetrical binary matrix *E*:

$$E = \begin{pmatrix} e_{11} & e_{12} & \cdots & e_{1n} \\ e_{21} & e_{22} & \cdots & e_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ e_{n1} & e_{n2} & \cdots & e_{nn} \end{pmatrix} \tag{5}$$

where n is the number of the stock markets and $e_{i,j} \in \{0,1\}$. If there is disaster-driven financial contagion between market i and market j, then $e_{i,j} = 1$; otherwise, $e_{i,j} = 0$. To test the existence of disaster-driven

[4] https://www.mathworks.com/help/econ/specify-gjr-models-using-gjr.html

financial contagion and construct the asymmetrical binary matrix E , the dynamic mixture copula-EVT model is estimated, and lower tail dependence is used as the measurements of disaster-driven financial contagion. Specifically, we formulate a hypothesis to examine the existence of disaster-driven financial contagion as follows:

$$\begin{cases} H_0: \bar{\lambda}_{crisis} \leq \bar{\lambda}_{pre-crisis} \\ H_1: \bar{\lambda}_{crisis} > \bar{\lambda}_{pre-crisis} \end{cases} \tag{6}$$

where $\bar{\lambda}_{crisis}$ and $\bar{\lambda}_{pre-crisis}$ are the dependence coefficients in the lower tail for the disaster and pre-crisis periods, respectively. The Fisher's z-transformation is used to test the hypothesis.

4.2. NETWORK CENTRALITY MEASURES

Measuring and analyzing structural metrics in the complex network is important for a deep understanding of financial contagion characteristics and systemic importance. We investigate four centrality measures (Wang et al., 2017; Liu et al., 2020), which are commonly used in network analysis, degree centrality, clustering coefficient centrality, closeness centrality, eigenvector centrality, and betweenness centrality. These centrality measures emphasize different structural aspects and represent different points of view. We include the detailed description of the centrality measures in Appendix 2.

Section 5: Data Description and Empirical Analysis

5.1. DATA AND DESCRIPTIVE STATISTICS

As our aim is to investigate the financial contagion of disaster events on financial markets, we will need to collect both the financial data and the disaster data. We propose to use the Emergency Events Database (EM-DAT) (https://public.emdat.be) for the data on disasters and their impacts. EM-DAT contains essential core data on the occurrence and effects of over 22,000 mass disasters in the world from 1900 to the present day.

Larger countries have a higher probability of experiencing a natural event, which will always influence the economic and financial markets within the country (Gassebner et al., 2010). We consider the disasters that occurred since 2000 in the US and analyze the financial contagion of disaster events on the US financial markets. However, as already pointed out by Gassebner et al. (2010), many of the disasters recorded in the EM-DAT dataset seemed to cause few casualties or damages. It is conceivable that many of the disasters included in EM-DAT may not have any impact on the financial markets. For a disaster to have an empirically impact, it should be of a magnitude that can directly cause widespread damage to the economy and financial system within a country. For this reason, 10 types of disasters including earthquakes, transport accidents, epidemics, miscellaneous accident, storms, extreme temperatures, industrial accidents, drought, flood, and wildfires are considered, and the serious disaster event which caused the greatest loss on economic or the greatest number of people reported affected or killed in each types of disasters is used as the analyzed sample. The major disaster events considered are the 2001 earthquake, 2001 transport accident (Airbus-300), 2002 West Nile Fever, 2003 fire accident, 2005 Hurricane Katrina, 2006 heat wave, 2010 oil spill event oil platform “Deepwater Horizon”, 2012 drought, 2016 flood, and 2018 Camp fire, which are described in Table 2.

Table 2
DISASTER EVENTS

Rank	Disaster Type	Event	Notation	Date	Number of Casualties	Damages (Billion)
1	Earthquake	Earthquake	Earth	Feb. 28, 2001	1 died, 400 affected	200
2	Transport accident	Airbus-300	Airb	Nov. 12, 2001	265 died, 16 affected	/
3	Epidemic	West Nile Fever	WNF	Jul. 9, 2002	214 died, 3523 affected	/
4	Miscellaneous accident	Nightclub fire	Nigh	Feb.20, 2003	100 died, 150 affected	/
5	Storm	Hurricane Katrina	Hurr	Aug. 29, 2005	656 died, 27 million affected	125
6	Extreme temperature	Heat wave	Heat	Jul. 14, 2006	164 died	/
7	Industrial accident	Oil spill	Oils	Apr. 20, 2010	11 died, 17 affected	20
8	Drought	Drought	Drou	Jun. 1, 2012	/	20
9	Flood	Flood	Flood	Aug.9, 2016	13 died, 70000 affected	10
10	Wildfire	Camp fire	Camp	Jun.1, 2018	88 died, 2500 affected	16.5

Notes: The event name of oil spill is called Oil platform Deepwater Horizon. "/" Data are not available.

As for the US financial market, we consider 30 sector indices of the US stock market before and after the aforementioned events as the sample. The 30 sector indices are listed in Table 3. Furthermore, we select six months before and after each major disaster event as the sample period. The daily average value-weighted returns in the 30 sector indices are obtained from Kenneth R. French's database)http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html.

Table 3
SECTOR NAME

Sector	Notation	Sector	Notation	Sector	Notation
Apparel	Appa	Consumer	Conu	Other	Other
Automobiles	Auto	Electrical	Elec	Paper	Paper
Beer	Beer	Fabrication	Fabr	Retail	Rtail
Books	Books	Financial	Fina	Services	Serv
Business	Busi	Food	Food	Smoke	Smoke
Carry	Carry	Games	Game	Steel	Steel
Chemicals	Chem	Healthcare	Heal	Textiles	Text
Coal	Coal	Meals	Meal	Transportation	Tran
Communication	Comm	Mines	Mine	Utilities	Util
Construction	Cons	Oil	Oil	Wholesale	Whol

Notes: The sector "other" includes sanitary services, steam and air conditioning supplies, irrigation systems, and cogeneration.

Table 4 presents the descriptive statistics for daily returns of 30 sectors from the period of January 1, 2000 to November 30, 2021. Note that the communication sector has the lowest mean with 0.019, while the coal sector has the highest standard deviations. These descriptive statistics indicate that there are lower returns for the communication sector, while the coal sector is more volatile. Besides, the Jarque-Bera statistics for each sector are significant at the 1% level that rejects the null-hypothesis of Gaussian distribution for the series. In addition, the augmented Dickey Fuller (ADF) test results indicate that all the return series are stationary at the 1% confidence level. Finally, the Ljung-Box Q (LBQ) and ARCH tests show the presence of autocorrelation and heteroscedasticity at the 10% significance level. Thereby, we can use the copula-EVT model to estimate the upper and lower tail dependence.

Table 4
DESCRIPTIVE STATISTICS OF SECTOR RETURN

Sector	Mean	Std	Jarque-Bera	ADF	LBQ	ARCH
Food	0.039	1.015	21236.804***	-80.230***	49.795***	1288.406***
Beer	0.041	1.139	35321.088***	-79.984***	49.557***	1554.526***
Smoke	0.069	1.478	27658.760***	-75.888***	4.488	508.670***
Games	0.057	1.809	8033.230***	-72.057***	18.133***	1052.249***
Books	0.021	1.533	28290.447***	-75.485***	6.239	819.687***
Consumer	0.034	1.114	97411.221***	-80.474***	71.435***	488.008***
Apparel	0.063	1.603	10131.415***	-74.634***	15.166***	919.105***
Healthcare	0.041	1.159	9819.357***	-77.830***	29.863***	1288.428***
Chemicals	0.048	1.567	11642.399***	-78.038***	22.400***	1296.260***
Textiles	0.047	2.011	41863.747***	-71.557***	17.271***	743.084***
Construction	0.050	1.707	14933.129***	-74.532***	9.688*	1381.355***
Steel	0.036	2.276	7917.513***	-75.507***	6.263	1225.890***
Fabrication	0.057	1.737	8650.066***	-77.468***	18.915***	1411.614***
Electrical	0.043	1.681	11785.652***	-77.106***	16.298***	1225.072***
Automobiles	0.057	1.950	9985.035***	-73.941***	24.998***	1042.828***
Carry	0.051	1.624	34977.344***	-74.395***	14.779**	1229.939***
Mines	0.053	2.008	9477.118***	-74.725***	10.136*	1344.722***
Coal	0.050	3.214	5364.99***	-72.504***	13.680**	981.184***
Oil	0.042	1.808	35651.4***	-79.702***	36.111***	1143.756***
Utilities	0.043	1.214	55949.785***	-80.232***	50.310***	1667.858***
Communication	0.019	1.349	21246.371***	-77.967***	17.099***	1214.724***
Services	0.040	1.532	10360.974***	-79.360***	31.411***	1062.032***
Business	0.045	1.833	10394.745***	-77.120***	16.410***	833.049***
Paper	0.036	1.281	8857.279***	-79.107***	27.516***	1246.627***
Transportation	0.049	1.466	11667.164***	-76.967***	13.616***	922.494***
Wholesale	0.041	1.271	15416.252***	-77.337***	10.890*	1541.389***
Rtail	0.047	1.321	8007.007***	-77.227***	24.306***	777.445***

Meal	0.055	1.300	36040.972∗∗∗	-76.520∗∗∗	8.983	1141.605∗∗∗
Financial	0.042	1.721	39267.083∗∗∗	-82.653∗∗∗	80.039∗∗∗	1200.03∗∗∗
Other	0.026	1.406	18210.155∗∗∗	-78.011∗∗∗	28.087∗∗∗	990.584∗∗∗

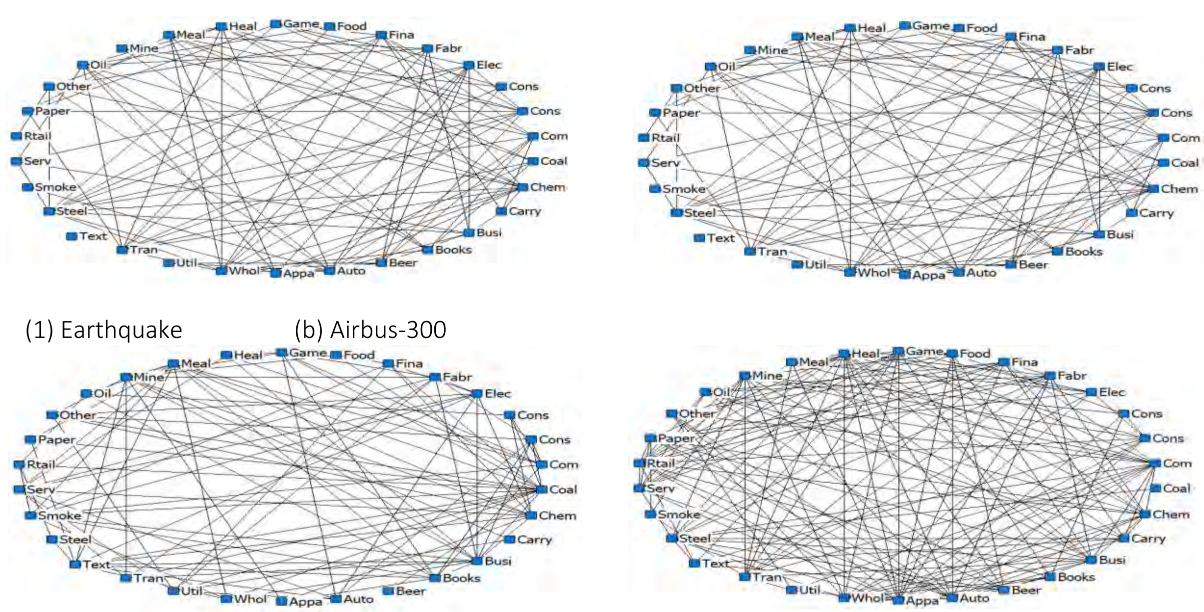
5.2. EMPIRICAL ANALYSIS: DISASTER-DRIVEN FINANCIAL CONTAGION DETECTION

As previously discussed, we first use the AR-GJR-EVT model to estimate the marginal distribution. Then the suitable copula will be selected to estimate the dependence between any two sectors. Considering that the lower tail dependence and upper tail dependence are the main measurements in this study, the copula functions that describe both the upper and lower tail dependence are preferred. Therefore, we use four dynamic mixture copulas, dynamic Clayton-Gumbel, dynamic Clayton-survival Clayton, dynamic Gumbel–survival Gumbel, and dynamic Symmetric–Joe Clayton (DSJC), to measure lower tail and upper tail dependence. For each pair of sectors, the four dynamic mixture copula-EVT models are estimated using the maximum likelihood estimation method. According to the Akaike information criterion, the best fitting copula is selected and the tail dependence coefficients for each pair of sectors are estimated.

We then use the 10% significance level to verify the existence of disaster-driven financial contagion and then construct the disaster-driven financial contagion network as shown in Figure 5 which provides a visual expression of disaster-driven financial contagion between any two sectors in each disaster event. As the existence of financial contagion would make sectors more exposed to risk and weaken the advantage of portfolio diversification, the result has great practical importance for investors to make decisions regarding portfolio selection.

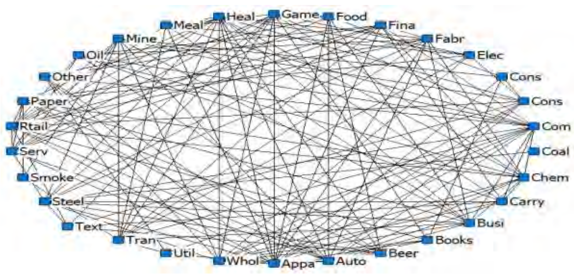
Figure 5

DISASTER-DRIVEN FINANCIAL CONTAGION NETWORK AMONG SECTORS IN THE DISASTER EVENTS

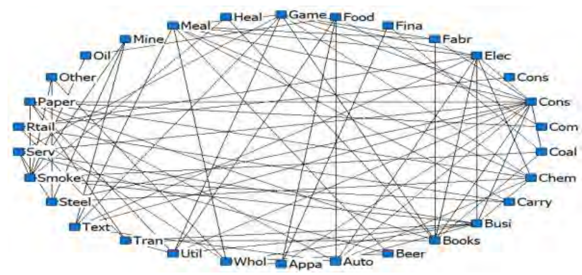


(1) Earthquake (b) Airbus-300

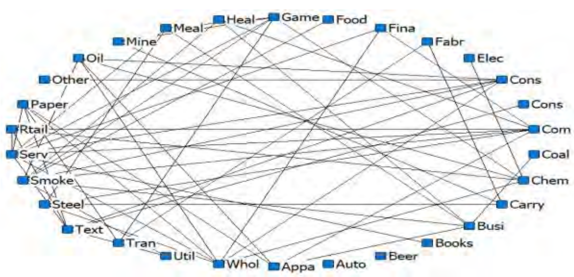
(c) West Nile Fever (d) Nightclub fire



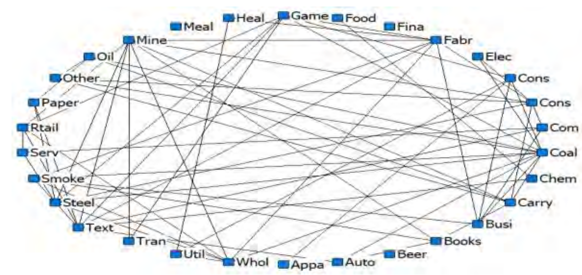
(e) Hurricane Katrina



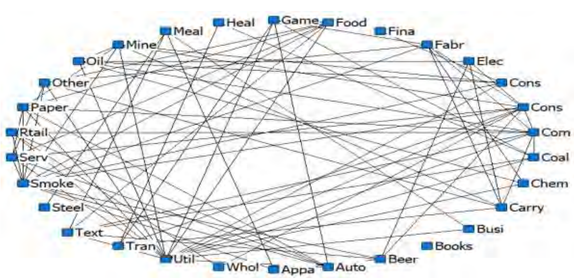
(f) Heat wave



(g) Oil spill



(h)Drought



(i) Flood

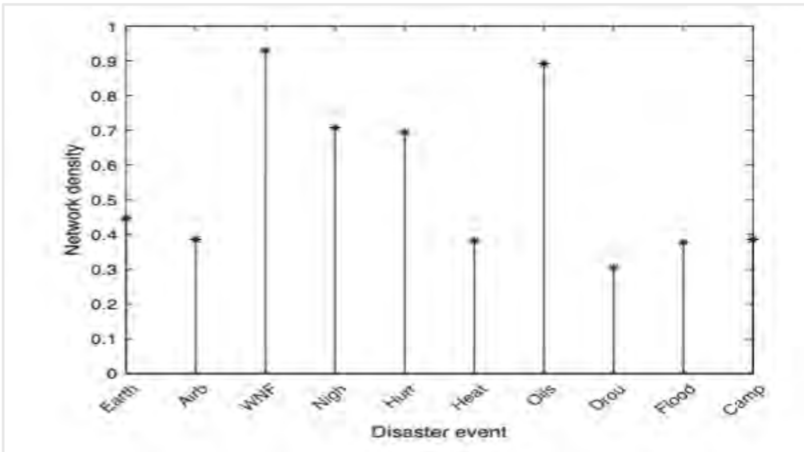
(j) Camp fire

5.3. CENTRALITY ANALYSIS OF DISASTER-DRIVEN FINANCIAL CONTAGION

Figure 6 shows the network density of the disaster-driven financial contagion network for each disaster event. It clearly shows that the network density changes under different types of disaster events. For instance, the network densities for West Nile Fever (WNF) and oil spill (Oils) events are the highest and greater than 0.9, while the drought (Drou) event has the smallest network density less than 0.4. These indicate that the West Nile fever and oil spill events cause severe damage to these sectors and are the easiest to drive financial contagion between sectors, while the drought event has the lowest influence on the sectors, consistent with the fact that the drought tends to be normalizing due to its high frequency, long duration, and wide range of influence.

Figure 6

NETWORK DENSITY FOR EACH DISASTER EVENT

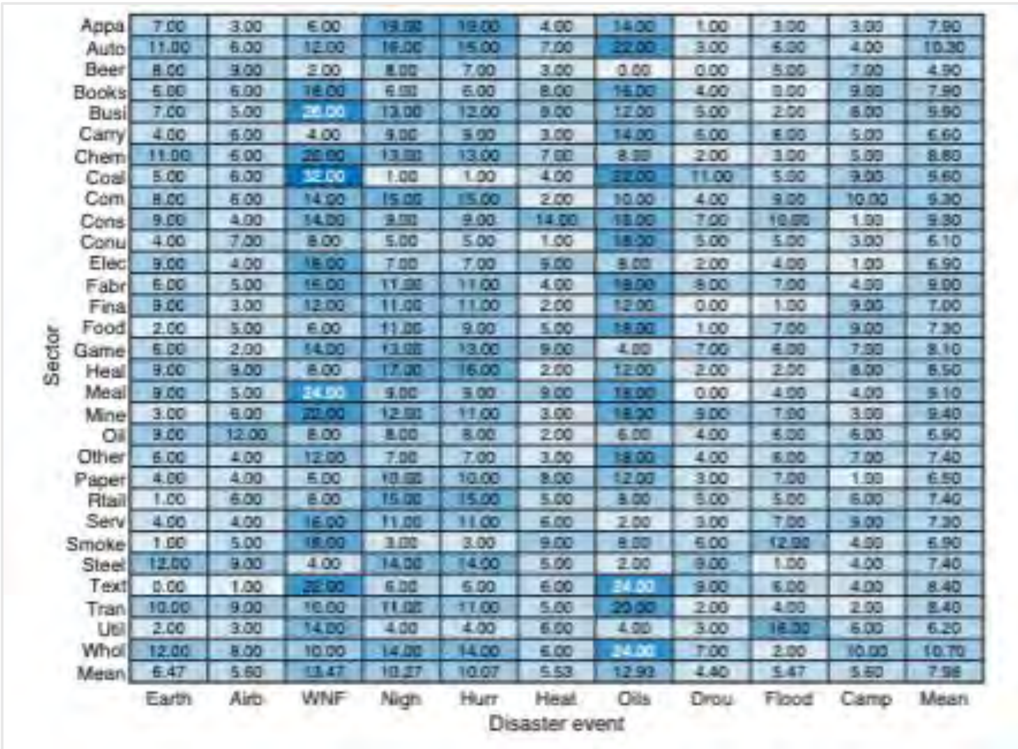


Note: The corresponding full name for each disaster event is presented in Table 3.

We now investigate centrality measures to quantify the topological features of the disaster-driven financial contagion network. Figure 7 demonstrates the values of the degree centrality for the sectors during the ten disaster events, which reveals different responses of different sectors to systemic risks under different types of disaster events. We also include figures of all four centrality measures (degree centrality, closeness centrality, betweenness centrality, eigenvector centrality) in Appendix 2. From Figure 7, we can see that with the darkest color in the first column, steel and auto sectors have the highest values for the degree centrality measure in the earthquake (Earth) event, while these values for the oil sector in the second column (Airbus-300 (Airb) event) are the highest. This shows that the steel and automobile sectors are critical nodes of risk contagion network when the earthquake event occurs. They are seriously influenced and the financial contagion from them is faster and stronger, while the oil sector has a similar importance in the Airbus-300 event and plays an important role for the spread of financial contagion. To prevent the spread of systemic risk contagion, it is necessary to implement dynamic supervision according to the nature of disasters. On the other hand, the values of the degree centrality measure are 0 for the textile sector in the earthquake, for the beer sector in the oil spill, and for the book sector in the flood. This phenomenon confirms that the textile, beer, and book sectors will not be influenced by corresponding disaster events, and they can be used as the principal risk diversifiers. Sectors with higher centrality measures should be put under special supervision and those with the value 0 of centrality measures should be considered as the risk diversifiers.

Figure 7

DEGREE CENTRALITY VALUES FOR THE NODES OF NETWORKS.



Note: The areas with darker blue in the map represent sectors with stronger centrality. The corresponding full names for each sector and disaster event are presented in Table 2 and Table 3

5.4. FINANCIAL CONTAGION CHANNEL DETECTION

We next turn to determine the transmission channels for these contagious sectors for each disaster event. As discussed previously, if the co-movement is stronger in extreme market downturns than in extreme market upturns, the financial contagion is driven by the wealth effect due to the presence of liquidity constraints during extreme market downturns. Conversely, if crises spread due to portfolio rebalancing behavior, co-movements are expected to be equal or weaker in extreme market downturns than in extreme market upturns. Similar to the work of Jayech (2016) and Horta et al. (2016), we use the mean lower tail dependence coefficient and mean upper tail dependence coefficient obtained from the dynamic mixture copula-EVT model to capture the dependence for extreme market downturns and upturns. Therefore, the hypothesis to check whether the financial contagion is caused by the wealth effect or by portfolio rebalancing can be formulated as:

$$\begin{cases} H_0 : \bar{\lambda}^L_{disaster} \leq \bar{\lambda}^U_{disaster} \\ H_1 : \bar{\lambda}^L_{disaster} > \bar{\lambda}^U_{disaster} \end{cases} \quad (7)$$

where $\bar{\lambda}^L_{disaster}$ and $\bar{\lambda}^U_{disaster}$ are the mean lower and upper tail dependence coefficients during the disaster period for all pairs of contagious markets, respectively.

Fisher's z-transformation is used to test this hypothesis, the results for the contagion channels

in the disaster events are provided in Table 5. The z-statistic is positive and significant at

the 5% level in all disaster events except in the West Nile fever event. This indicates that the financial contagion between sectors in these disaster events is spread through the wealth effect, except the spread through portfolio rebalancing in the West Nile fever event. This finding shed light on the transmission mechanism of the financial contagion driven disaster events between sectors and is helpful for risk managers to prevent the spread of risk driven by disaster events. To avoid financial contagion driven by the West Nile fever event, risk managers can impose limits on capital movements to mitigate the effect of financial contagion, since the risk from the West Nile fever event is spread through rebalancing behavior. Moreover, risk managers can provide timely support for struggling financial sectors to reduce investors' perceived risk to avoid the spread of financial contagion driven by the other disaster.

Table 5
FINANCIAL CONTAGION CHANNELS

Disaster	$\overline{\lambda}^{U}_{disaster}$	$\overline{\lambda}^{L}_{disaster}$	z-statistic	p	Conclusion
Earthquake	0.141	0.494	3.130	0.001	Wealth effect
Airbus-300	0.161	0.438	2.409	0.008	Wealth effect
West Nile fever	0.307	0.372	0.583	0.280	Portfolio Rebalancing
Nightclub fire	0.257	0.459	1.830	0.034	Wealth effect
Hurricane Katrina	0.259	0.459	1.812	0.035	Wealth effect
Heat wave	0.152	0.508	3.208	0.001	Wealth effect
Oil spill	0.203	0.582	3.616	0.000	Wealth effect
Drought	0.223	0.484	2.550	0.005	Wealth effect
Flood	0.160	0.478	2.812	0.002	Wealth effect
Camp fire	0.059	0.558	4.449	0.000	Wealth effect

5.5. DISCUSSION ON DISASTER-DRIVEN EMPIRICAL ANALYSIS

Financial contagion driven by disasters has a damaging impact on portfolio diversification. Our study will be of a certain interest to investors and policymakers as it allows a better understanding of the disaster-driven financial contagion between sectors. According to our contagion results, both the sector characteristics and the nature of the disasters are important to investors wishing to utilize the safest sectors in their portfolios. ``Thematic'' portfolios that focus on specific sectors might turn out to be particularly risky for sectors that are known to be particularly sensitive to financial contagion driven by disasters, such as automobile and wholesale sectors. On the other hand, the investor should give a specific focus on the West Nile fever and oil spill events as it is easier to spread financial contagion across sectors. Moreover, the investors also can effectively predict the future trend of the market by analyzing the contagion characteristics of the sectors in each type of disaster event, which contributes to their asset allocation and investment decisions. The sectors themselves can maintain the stable growth of market value by improving innovation ability and realizing industrial transformation and upgrading. Finally, our results also provide important insights for risk managers to forestall and defuse the spread of financial contagion according to the analysis of the contagion channel on different types of disaster events.

Section 6: Conclusion

Disasters have significant economic and financial effects in which they occur and would increase investors' risk perception that spreads the disaster risk (Huang et al., 2022). In this paper, we investigate the contagion effect of several types of disaster events since 2000 on the US sectors. We utilize the dynamic mixture copula-EVT model and the complex network approach to detect the existence of disaster-driven financial contagion, quantitatively analyze the contagion characteristics, and determine the contagion channel during these disaster events.

Our results confirm the existence of financial contagion during all disaster events and show heterogeneous responses of different sectors to different types of disaster events. The West Nile fever and oil spill events are found to be the easiest to drive financial contagion, while the drought disaster has the least influence on the markets. Moreover, the automobile and wholesale sectors are the most affected by disasters and are found to be highly risky. They are the most important sectors in the disaster-driven financial contagion network and the contagion from the two sectors is the easiest, fastest, and strongest in the disaster events. In addition, we also find that the textile sector in an earthquake, the beer in an oil spill, the beer, financial, and meal sectors in a drought, and the book sector in a flood are immune to financial contagion and therefore are capable to diversify the tail risk. This finding provides essential insights for investors to design risk hedging strategies during disaster events.

Finally, the financial contagion between sectors in these disaster events is found to be spread through the wealth effect, except the financial contagion in the West Nile fever event that is spread through the portfolio rebalancing. To limit the contagion associated with wealth constraints, the international financial risk managers could provide timely support to the struggling financial institutions so as to reduce investors' perceived risk. Also, policymakers and experts may reevaluate the global financial system regulation and take appropriate reactions to limit the recession. Our findings shed light on the transmission mechanism of the disaster event on the sectors.

This research focuses on the disaster-driven financial contagion among the sectors in the US stock market based on the 10 types of disaster events that happened in the US. For future research, the disaster events can be expanded to include the monetary policy event, virus event, bank default event, and terrorist attack events in other major economies, such as the UK, China, and Japan. Moreover, we can further investigate the disaster-driven financial contagion across other important asset classes including foreign exchange, credit derivatives, and energy markets, and the impact of macroeconomics such as financial links on the disaster-driven financial contagion.

During the disaster-driven financial turmoil, it is possible to observe the flight-to-quality phenomenon occurring when investors sell what they perceive to be higher-risk investments and purchase perceived safe haven investments in a market crash. Additionally, the increasing cost of natural disasters is also accomplished with the increasing importance of environmental, social, and governance (ESG) investment as a potential new “safe-haven” asset. In future work, we could also use the diagonal tail dependence as the measure of potential flight-to-quality, i.e., the negative extreme dependence across markets during the financial contagion and the role of ESG investing in such contagion.

Section 7: Acknowledgments

The researchers' deepest gratitude goes to those without whose efforts this project could not have come to fruition: the Project Oversight Group for their diligent work overseeing, reviewing and editing this report for accuracy and relevance.

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Appendix 1

Now that we have different types of copulas that can capture different types of tail dependences, we can introduce the unified version of copulas that can handle both upper tail and lower tail dependence as well as independence in one functional form, which is called dynamic mixture copula. We select four dynamic mixture copulas, dynamic Clayton-Gumbel, dynamic Clayton-survival Clayton, dynamic Gumbel–survival Gumbel, and dynamic Symmetric–Joe Clayton (DSJC), to measure tail dependence. The copula function C and the corresponding lower and upper tail dependence coefficients regarding the four dynamic mixture copula-EVT models are detailed as follows.

The dynamic Clayton-Gumbel copula (CDCG) is expressed as

$$C^{DCG}(u,v;k^C,k^G)=\omega C^{DC}(u,v;k^C)+(1-\omega)C^{DG}(u,v;k^G), \quad (8)$$

where ω is the weight parameter with ω ∈ [0,1], and CDC and CDG are the dynamic Clayton copula and dynamic Gumbel copula, respectively. The evolution process of the dependence parameters k^C and k^G in Eq. (5) are defined as

$$k_t^C = \left(w_1+\beta_1 k_{t-1}^C+\alpha_1\cdot\frac{1}{10}\sum_{i=1}^{10}|u_{t-i}-v_{t-i}|\right)^2, \quad (9)$$

$$k_t^G = 1+\left(w_2+\beta_2 k_{t-1}^G+\alpha_2\cdot\frac{1}{10}\sum_{i=1}^{10}|u_{t-i}-v_{t-i}|\right)^2, \quad (10)$$

where $k_t^C\in[0,+\infty)$ and $k_t^G\in[1,+\infty)$. The dependence coefficients of the lower tail and upper tail at time t are correspondingly given by: $\lambda_t^L=\omega\cdot 2^{-1/k_t^C}$, $\lambda_t^U=(1-\omega)\cdot(2-2^{1/k_t^G})$.

The dynamic Clayton-survival Clayton copula (CDCSC) is expressed as

$$C^{DCSC}(u,v;k^C,k^{SC})=\omega C^{DC}(u,v;k^C)+(1-\omega)C^{DSC}(u,v;k^{SC}), \quad (11)$$

where CDC and CDSC are the dynamic Clayton copula and dynamic survival Clayton copula, respectively. The evolution process of the dependence parameters k^C and k^{SC} in Eq. (8) are defined as

$$k_t^C = \left(w_1+\beta_1 k_{t-1}^C+\alpha_1\cdot\frac{1}{10}\sum_{i=1}^{10}|u_{t-i}-v_{t-i}|\right)^2, \quad (12)$$

$$k_t^{SC} = \left(w_2+\beta_2 k_{t-1}^{SC}+\alpha_2\cdot\frac{1}{10}\sum_{i=1}^{10}|u_{t-i}-v_{t-i}|\right)^2, \quad (13)$$

where k_t^C ∈ [0, + ∞) and k_t^{SC} ∈ [0, + ∞). The dependence coefficients of the lower and upper tails at time t are accordingly given by: λ_t^L = ω · 2−1/k_t^C, λ_t^U = (1 − ω) · 2−1/ k_t^{SC}.

The dynamic Gumbel–survival Gumbel copula (CDGSG) is expressed as

$$C^{DGSG}(u,v;k^{SG},k^G)=\omega C^{DSG}(u,v;k^{SG})+(1-\omega)C^{DG}(u,v;k^G), \quad (14)$$

where C^{DSG} and C^{DG} are the dynamic survival Gumbel copula and dynamic Gumbel copula, respectively. The evolution process of the dependence parameters k^{SG} and k^G in Eq. (11) are defined as

$$k_t^{SG} = 1 + \left(w_1 + \beta_1 k_{t-1}^{SG} + \alpha_1 \cdot \frac{1}{10} \sum_{i=1}^{10} | u_{t-i} - v_{t-i} | \right)^2 , \tag{15}$$

$$k_t^{G} = 1 + \left(w_2 + \beta_2 k_{t-1}^{G} + \alpha_2 \cdot \frac{1}{10} \sum_{i=1}^{10} | u_{t-i} - v_{t-i} | \right)^2 , \tag{16}$$

where $k_t^{SG} \in [1, +\infty)$ and $k_t^{G} \in [1, +\infty)$. The dependence coefficients of the lower and upper tails at time t are accordingly given by: $\lambda_t^L = \omega \cdot (2 - 2^{1/k_t^{SG}})$, $\lambda_t^U = (1-\omega) \cdot (2 - 2^{1/k_t^{G}})$.

The DSJC copula (CDSJC) is expressed as

$$C^{DSJC}(u, v; \lambda^U, \lambda^L) = \omega C^{JC}(u, v; \lambda^U, \lambda^L) + (1-\omega)(C^{JC}(1-u, 1-v; \lambda^U, \lambda^L) + u + v - 1), \tag{17}$$

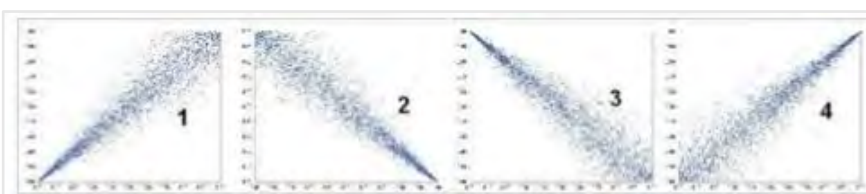
where C^{DJC} is the dynamic Joe Clayton copula. The dynamic evolution equations of the tail dependence coefficients λ^U and λ^L in Eq. (14) are accordingly specified as

$$\lambda_t^U = \wedge \left(w_1 + \beta_1 \lambda_{t-1}^U + \alpha_1 \cdot \tfrac{1}{10} \textstyle\sum_{i=1}^{10} |u_{t-i} - v_{t-i}| \right), \tag{18}$$

where $\wedge(x) = (1 + e^x)^{-1}$.

We also construct variations of the dynamic mixture copulas to model the upper-lower and lower-upper tail dependence through the 90-degree counterclockwise rotation of dynamic mixture copulas. The best-fitting dynamic mixture copula is selected based on the Akaike information criteria and Bayesian information criteria.

Figure 4
ILLUSTRATION OF ROTATION OF DYNAMIC MIXTURE COPULAS



Appendix 2

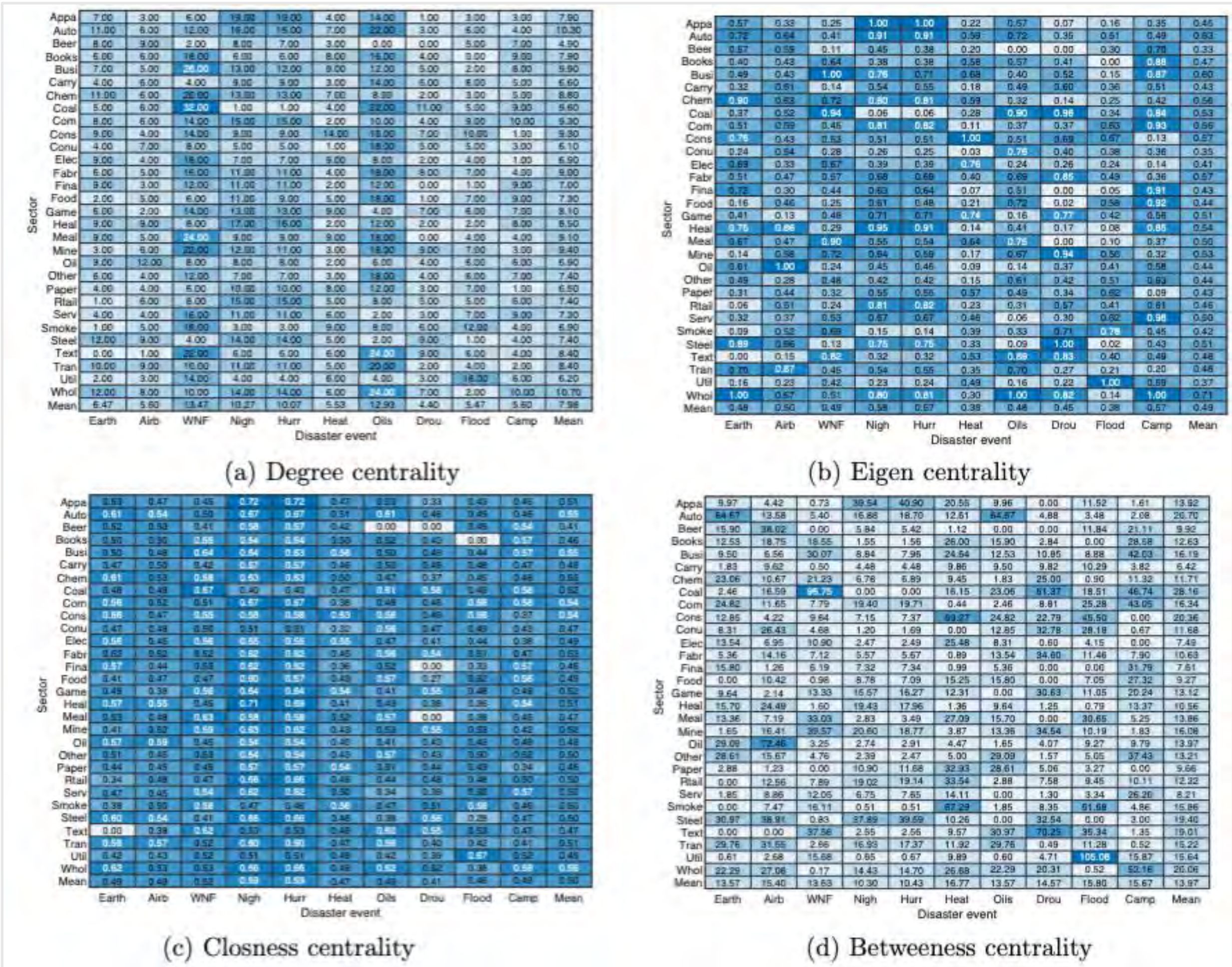
(1) Degree centrality. The degree of a node is defined as the number of all edges connected to the nodes. In terms of the adjacency matrix E with elements, the node degree indexed i can be formalized as: $D_i = \sum_{j=1, j \neq i}^{n} e_{i,j}$. The sector with a higher degree is more likely to exhibit financial contagion.

(2) Closeness centrality. Closeness centrality measures the speed of the information flow from a given node to other nodes. It is defined as the normalized inverse of the sum of the topological distances. For a node i with the shortest path between nodes i and j, the closeness centrality of node i is formalized as $CC(i) = \frac{N-1}{\sum_{i \neq j} d(i, j)}$. The sector with larger closeness centrality is faster to exhibit financial contagion in the network.

(3) Betweenness centrality. Betweenness centrality provides a way to detect the influence degree of a node on the information flow. In the case of betweenness centrality, a node is well connected if it is located on many of the shortest directed paths between other nodes. The betweenness centrality of node i is formulated as $BC_i = \sum_{j,k} g_{jk}(i) / g_{jk}$,where $i \neq j \neq k$, g_{jk} is the number of shortest paths connecting nodes j and k, and $g_{jk}(i)$ is the number of shortest paths connecting nodes j and k and node i is on.

(4) Eigenvector centrality. Eigenvector centrality assesses a node's systemic importance in the network. In terms of the adjacency matrix E with the largest eigenvalue λ, a node's eigenvector

centrality indexed i is defined as the sum of neighboring node j's eigenvector centralities and can be formalized as: $EC(i) = \frac{1}{\lambda} \sum_{j} e_{ij} EC(j)$. The financial market with higher eigenvector centrality implies a greater contagion strength in the network.



(a) Degree centrality

(b) Eigen centrality

(c) Closness centrality

(d) Betweeness centrality

From the mean values of the four centrality measures in the last row of the four sub-figures, the financial contagion is easier to spread during the West Nile fever and oil spill events, while that is stronger and faster during the nightclub fire and hurricane Katrina. On the other hand, the mean values of the four centrality measures in the last column show that the automobile and wholesale sectors are mostly affected by the ten types of disaster events, they are the easiest to spread financial contagion, and the contagion for them is the fastest and strongest. The beer and carry sectors suffer a smaller impact and show risk diversification effects. For this reason, to prevent systemic risk contagion driven by disaster events, it is necessary to strengthen the supervision of the automobile and wholesale sectors. Overall, our results verify that the automobile and wholesale sectors are the most affected, while the beer and carry sectors are relatively safe from financial contagion driven by disasters.

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