Energy Economics 110 (2022) 106054

Contents lists available at ScienceDirect

Energy Economics

journal homepage: www.elsevier.com/locate/eneeco

Extreme co-movements between infectious disease events and crude oil futures prices: From extreme value analysis perspective

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ARTICLE INFO

Keywords:
COVID-19
Crude oil futures market
Tail risk contagions
Autoregressive conditional Fréchet model
Tail quotient correlation coefficient

ABSTRACT

This paper examines the extreme co-movements between infectious disease events and crude oil futures through extreme value analyses. We contribute to the literature by providing a novel framework of tail risk early warning and considering infectious diseases as a systemic risk factor for crude oil futures. The results provide evidence that: (1) when an extreme event occurs, the tail index of the infectious disease reaches its empirical lower threshold, which is approximately 2.30; (2) when a jump in volatility corresponding to the severeness of the epidemic is observed, the tail index reaches the lower bound, but not reversely; (3) both upside and downside extreme co-movements exist, whereas they are asymmetric; and (4) each tail quotient correlation coefficient keeps rising and reaches a peak before crises and fall sharply with the collapse of crude oil markets. The findings can offer implications for government officials, investors, portfolio managers, and policymakers, respectively.

1. Introduction

Infectious diseases are critical to extreme movements in financial asset prices (Ozili and Arun, 2020; McKibbin and Fernando, 2021; Lai and Zhang, 2020). In the past two decades, infectious diseases like SARS, bird flu, Ebola virus, and the coronavirus (COVID-19) have raged in local areas and spread around the world, reducing economic development regionally and globally. In the first half of 2020, the global spread of the COVID-19 led to a slowdown in economic activity in many important economies and production suspension in some industrial cities such as Wuhan, China, which profoundly changed the global industrial, energy, and economic structures.

The outbreak and rapid spread of COVID-19 not only severely affected economic activities like firm performance (Fu and Shen, 2020; Shen et al., 2020; Hu and Zhang, 2021), household consumption (Liu et al., 2020a), and labor force participation rate (Yu et al., 2020), but also deeply affected global financial markets. During the pandemic, abrupt changes in returns structures and resistances are found in many assets, such as stocks (Mishra et al., 2020; Zhang et al., 2020), crude oil prices (Gil-Alana and Monge, 2020), exchange rates (Narayan, 2020a), and the option-based volatility (VIX) index (Vera-Valdés, 2021). Normally, the impacts of the pandemic on asset volatilities are asymmetrical (Li, 2021).

Responding to the COVID-19, energy derivative prices fluctuated sharply as well. Crude oil prices went down fiercely at the beginning of 2020, with the market sentiments changing significantly (Huang and Zheng, 2020). The most notable extreme event might be the “negative price” of WTI on April 20, 2020, when the main contract of WTI crude oil futures (expired on April 21, delivery in May) fell by USD$55.90/barrel to USD$-37.63/barrel, a drop of 306%. It was the first time in history that a crude oil future closed at a price below zero. The “negative price” event implies that the extreme shocks of infectious diseases on asset prices can no longer be ignored.

In the literature, how energy futures prices are linked with economic factors is a hot topic. For example, risk spillover effects have been evidenced between crude oil prices and stocks, exchange rates, metals, agricultural commodities, and cryptocurrencies (see Section 2 for the literature review). Whereas the existing studies do lay a valuable basis for related topics, there are still three notable gaps in this field. First, the majority of the research focused on the linkages between crude oil futures and other financial markets, while the study focusing on the role of infectious diseases on crude oil future prices is relatively scarce. Second, most existing studies are based on averages rather than maxima or minima. Consequently, Gaussian models are used in those studies, which

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https://doi.org/10.1016/j.eneco.2022.106054
Received 11 September 2020; Received in revised form 12 March 2022; Accepted 25 April 2022
Available online 2 May 2022

may cause model misspecification problems under extreme circumstances like the COVID-19. This is because the second moments of variables may not exist in an extreme circumstance (Hansen, 1994), and thus extreme value analyses are supposed to be utilized. Third, the previous studies mainly discuss the volatility spillovers (the spillover effects in second moments) among assets. However, it should be noted that, in an extreme environment, co-movements of variables can be found in not only the volatility level (the second moment) but also the "tail level" (higher moments like skewness and kurtosis). The latter is the so-called "extreme co-movements" or "tail risk contagions."

This paper tries to fill the current gaps by utilizing the newly developed extreme value analysis (EVA) methods and introducing the following three novelties. First, different from most previous studies that focus on the relationships between crude oil futures and other financial markets, this paper directly investigates the linkage between crude oil futures and infectious diseases per se. Second, to avoid model misspecification under extreme environments, this paper converts the daily observations into monthly maxima sequences and uses contemporary EVA methods in the empirical study. We use an extreme value theory theorem (see Theorem 1 in Section 3.1) to ensure the correctness of the distribution selection and model setting in this paper. Third, to capture the risk spillover effects in higher moments, that is, to measure and quantify extreme co-movements and tail risk contagions, dynamic time series process (see Section 3.2) is used to model each monthly maxima sequence, and a novel tail quotient correlation coefficient (see Section 3.3) is utilized to model the spillover effects.

This paper contributes to the literature by introducing an advanced EVA approach and the GEV-AcF-TQCC framework in the interdisciplinary field of price analysis and risk analysis. First, in terms of price analysis and asset pricing, this paper considers extreme infectious diseases events as pricing factors for crude oil futures markets, which constitute the systemic risk premium. Second, the paper provides a framework of tail risk early warning in terms of risk management. Based on extreme value theory, we propose and utilize an econometric process for studying tail risk spillover, which is the so-called GEV-AcF-TQCC framework (see Section 3). Using this framework, the resulting AcF tail index can distinguish the "extreme time" from the "normal period," and the resulting dynamic tail quotient correlation coefficients can be used to signal possible crises in financial markets. Last but not least, our empirical finding may offer implications for government officials, investors, portfolio managers, and policymakers (see Section 7 for details).

The rest of the paper is organized as follows. Literature regarding risk spillover effects of crude oil futures markets is reviewed in Section 2. The econometric methodologies used in this paper are explained in Section 3. In Section 4, the infectious disease and crude oil futures data are described and analyzed. Section 5 reports the empirical results. Section 6 discusses the possible economic transmission mechanism behind our findings, which may provide research motivations for future studies. Section 7 concludes the paper and points out the implications of the findings.

2. Literature review

There is a lot of literature focusing on the spillover interaction between crude oil future prices and other assets, such as stocks, exchange rates, metals, agricultural commodities, and cryptocurrencies. We offer a brief review next.

The crude oil futures market has strong interactions with stocks and exchange rates. Lin et al. (2014) showed the risk spillover effect from the crude oil market to the Nigerian stock market. Basher and Sadorsky (2016) explained that crude oil is the best asset to hedge the risks in stock markets in emerging countries. Reboredo et al. (2017) studied co-movement and causality between oil and renewable energy stock prices using continuous and discrete wavelets. They found that dependence between oil and renewable energy returns in the short run was weak but gradually strengthened towards the long run, mainly for 2008–2012. Based on a nonparametric panel data model, Silvapulle et al. (2017) studied the co-movement of crude oil and stock markets in net oil-exporting economies. They found a significant relationship between these two assets. A similar conclusion can be found in Lin and Su (2020) by using the quantile-on-quantile approach. Tiwari et al. (2020) examined systemic risk and dependence between oil and stock market indices of G7 economies and found dissimilar dependence structures between returns series of oil and the G7 stock markets. Reboredo et al. (2014) examined the relationship between oil prices and the US dollar exchange rate using detrended cross-correlation analysis. They found that the negative dependence between oil and the US dollar increased after the onset of the global financial crisis for all time scales, thereby providing evidence of both contagion and interdependence.

Crude oil futures were also found to react to metal prices in extreme contexts. Reboredo (2012) estimated bivariate copulas to measure the dependence between crude oil and agricultural commodities and concluded that extreme oil price increases do not cause food price increases. Reboredo and Ugolini (2016) examined the impact of large upward/downward oil price movements on metal prices and the asymmetric response of metal prices to large oil price movements. They found that large downward and upward oil price movements had spillover effects on all these metals before and after the outbreak of the global financial crisis. Recently, Uddin et al. (2020) examined the characteristics of the risk spillover under extreme market scenarios between precious metals (gold, silver, platinum) and oil by using a copula approach and found symmetric co-movement under normal and extreme market scenarios.

Consequently, the movements of crude oil prices may present impacts on agricultural commodities and other energy-related assets. Nazlioglu et al. (2013) investigated the causality-in-variance among the wheat, corn, soybeans, sugar, and crude oil futures. They found no causality-in-variance from crude oil to food during the pre-food crisis period (2006–2008), but after 2008 the causality can be unidirectional or bidirectional. Hernandez (2014) used c-vines and d-vines copulas to study crude oil's symmetric and asymmetric dependence structure with natural gas, coal, and uranium. Shahzad et al. (2018) implemented ARMA-GARCH-Copula methods to examine the upside and downside tail spillovers between oil and agricultural commodities. They evidenced both symmetry in the tail dependence and asymmetry in spillovers from oil to agricultural commodities during financial turmoil.

The linkage between crude oil prices and cryptocurrency markets was also found. Huang et al. (2019) found that the Bitcoin market is susceptible to price fluctuations from gold and crude oil markets. Using the VAR-MGARCH-BEKK methods, Okorie and Lin (2020) find evidence of bidirectional volatility spillover between the crude oil market and Bit Capital Vendor.

Regarding the impact of COVID-19 on crude oil prices, Liu et al. (2020b) found that the COVID-19 pandemic had a positive effect on crude oil returns, which is contrary to our intuition. Qin et al. (2020) investigated the interrelationship between pandemics and oil prices. They found that the pandemics may reduce the oil demand, causing oil prices to decrease, which is inconsistent with the predictions of the intertemporal capital asset pricing model. To quantify the pandemic's effect by overcoming the lack of robustness, Narayan et al. (2021) proposed a new measure. For related issues regarding the connection between crude oil news and the pandemic, one can refer to Narayan (2020b).

3. Methodology

This paper utilizes the newly developed extreme value analysis (EVA) methods to examine the extreme co-movements between crude oil futures prices and infectious disease. The motivations for using EVA are in two aspects: (1) the topic; and (2) the data. Firstly, this paper aims to explore the tail risk spillovers among variables, and thus extreme analysis methods need to be used to illustrate extreme features of variables. Secondly, as can be seen from Table 2 and the results of the J-B tests, the data utilized in this paper is highly asymmetric and may not be normally distributed, thereby making it could be better examined using EVA rather than conventional Gaussian models.

In extreme value statistical analysis, two modeling ideas are most commonly applied: the first is to model the block maxima or minima, and the second is to model the observations that exceed a given threshold (Coles, 2001). This paper belongs to the first class. Before our econometric analysis, all variables are converted into monthly maxima (see Section 4). The modeling procedure in this paper includes three steps: (1) to fit the monthly maxima variables with generalized extreme value (GEV) distribution and yield the estimated location, scale, and shape parameters; (2) to fit the monthly maxima variables using the Autoregressive conditional Fréchet (AcF) model, and the dynamic volatilities and dynamic tail risk indexes can be obtained; and (3) to measure tail risk spillover effects using the tail quotient correlation coefficient (TQCC). To sum up, the modeling procedure of this study can be termed as a GEV-AcF-TQCC framework, which serves as a novelty of this paper and can be used for investigating other dynamic tail risk spillover issues.

3.1. The static modeling of monthly block maxima

In the paper, we use the generalized extreme value (GEV) distribution to fit the monthly maxima variables with full samples, and their domains of attraction can be investigated. According to Fisher and Tippett (1928), Gnedenko (1943), and Gumbel (1958), we present the following Theorem 1 without showing the proof which can be seen in the literature.

Theorem 1. *If there exist sequences of constants* $\{a_n > 0\}$ *and* $\{b_n\}$ such that

$$Pr\left\{\frac{M_n - b_n}{a_n} \le z\right\} \to G(z) \tag{1}$$

as $n \to \infty$ *for a non-degenerate distribution function G, then G is a member of the GEV family*

$$G(z) = exp\left\{-\left[1 + \xi\left(\frac{z-\mu}{\sigma}\right)\right]^{-\frac{1}{\xi}}\right\} \tag{2}$$

which is defined on $\{z : 1 + \xi(z - \mu)/\sigma > 0\}$, *where* $-\infty < \mu < \infty$, $\sigma > 0$, *and* $-\infty < \xi < \infty$.

In this study, each variable is a monthly block maximum sequence, and we will first use the GEV distribution to fit the full sample of the variables. Furthermore, the GEV distribution includes three subtypes, corresponding to different features in the tail regions:

Type I GEV: Gumbel distribution,

$$G(z) = exp\left\{exp\left[-\left(\frac{z-b}{a}\right)\right]\right\}, -\infty < z < \infty, a > 0, -\infty < b < \infty \tag{3}$$

Type II GEV: Fréchet distribution,

$$G(z) = exp\left\{-\left(\frac{z-b}{a}\right)^{-\alpha}\right\}, z > b, a > 0, \alpha > 0, -\infty < b < \infty \tag{4}$$

Type III GEV: Weibull distribution,

$$G(z) = exp\left\{-\left(-\frac{z-b}{a}\right)^{\alpha}\right\}, z < b, a > 0, \alpha > 0, -\infty < b < \infty \tag{5}$$

where $\alpha = 1/\xi$. For more details on GEV distribution, see Coles (2001). In this paper, we will further study the domains of attraction of each variable based on the shape parameters (see Section 5.1). The GEV parameters are estimated using maximum log-likelihood estimation (MLE) in this paper.

3.2. The dynamic modeling of monthly block maxima

Given that all variables of this study follow Fréchet distribution (see Section 5.1), we adopt a dynamic model for the maxima using the AcF (1,1) model (the Autoregressive conditional Fréchet model, see Zhao et al., 2018 for details) for each variable. The AcF (1,1) model is written as:

$$Q_t = \mu + \sigma_t Y_t^{\frac{1}{\alpha_t}} \tag{6}$$

$$log\sigma_t = \beta_0 + \beta_1 log\sigma_{t-1} + \beta_2 exp(-\beta_3 Q_{t-1}) \tag{7}$$

$$log\alpha_t = \gamma_0 + \gamma_1 log\alpha_{t-1} + \gamma_2 exp(-\gamma_3 Q_{t-1}) \tag{8}$$

where $\{Y_t\}$ is a sequence of *i.i.d.* unit Fréchet random variables, $0 \le \beta_1 \ne \gamma_1 < 1, \beta_2 < 0, \beta_3 > 0, \gamma_2 > 0$ and $\gamma_3 > 0$. $\{Q_t\}$ is the sequence of interest, which is a sequence of monthly block maxima with Fréchet location parameter μ, dynamic scale parameter sequence $\{\sigma_t\}$, and dynamic shape parameter sequence $\{\alpha_t\}$. This model can be estimated using conditional maximum likelihood estimation (cMLE), and the recovered values in $\{Y_t\}$ can be directly used for the extreme co-movements study (Zhang, 2008). In financial econometrics, this model can be used for generating extreme losses, pricing ad hoc financial assets, and modeling tail risk dynamics (Lin et al., 2021). The AcF (1,1) results are shown in Section 5.2.

3.3. The modeling of extreme co-movements and tail risk spillovers

Extreme co-movements refer to extreme values that co-occur during a very short period, and tail risk spillovers or tail risk contagions stand for the impact of one variable on another in terms of extreme values (Zhang, 2008). In this paper, we use the tail quotient correlation coefficient (TQCC), proposed by (Zhang, 2008), and theoretically studied by Zhang et al. (2017), to measure the tail spillover effects from infectious diseases to crude oil futures prices. The TQCC is defined next.

Definition 1. If $\{(X_i, Y_i)\}_{i=1}^n$ is a random sample of random variables being tail equivalent to unit Fréchet random variables (X, Y),

$$q_{u_n} = \frac{\max\limits_{1\le i\le n}\left(\frac{max(X_i,u_n)}{max(Y_i,u_n)} - 1\right) + \max\limits_{1\le i\le n}\left(\frac{max(Y_i,u_n)}{max(X_i,u_n)} - 1\right)}{\max\limits_{1\le i\le n}\frac{max(X_i,u_n)}{max(Y_i,u_n)} \times \max\limits_{1\le i\le n}\frac{max(Y_i,u_n)}{max(X_i,u_n)} - 1} \tag{9}$$

is the tail quotient correlation coefficient (TQCC) where u_n *is the varying threshold that tends to infinity.*

Note that the numerator in (9) is equivalent to the original form defined in Zhang et al. (2017). These two new forms clearly reveal that the TQCC studies maximum relative errors at tails, while many other existing measures, e.g., linear correlation coefficients, are defined based on absolute errors. Moreover, the new forms make interpretations easy and straightforward.

Intuitively, TQCC is a measure of tail dependence or extreme co-movement, characterized by relative errors at tails, between two random variables. It ranges in [0,1], with its lower bound and upper bound standing for tail independent and completely dependent, respectively. The value of TQCC indicates the chance of one variable reaching its extreme value (exceeding the threshold), given that the other variable has reached its extreme value, i.e., it approximates $P(X_i > u| Y_i > u)$ as $u \to \infty$; see Zhang et al. (2017). For example, if the TQCC between X and Y is 0.2019, this means that given that Y has reached its extreme value, the chance that X also reaches its extreme value is 20.19%.

To test tail independence, i.e., no extreme co-movements or tail spillovers, among variables, we apply the gamma test method proposed by Zhang (2008). This test can be generalized to the Chi-square test (Zhang et al., 2017), and their results are consistent. Based on the computed TQCC, we can formulate the following hypothesis test of independence:

H_0^c : X and Y are tail independent.

H_1^c : X and Y are tail dependent.

here the superscript c means that the complete data are used for this test. Under H_0^c, we have the following theorem (Zhang, 2008):

Theorem 2. *If X and Y are tail independent and have unit Fréchet margins, and* (X_i, Y_i), $i = 1, 2, \cdots, n$ *is a random sample from* (X, Y), *then random variables* $max_{i \le n}(Y_i/X_i)$ *and* $min_{i \le n}(Y_i/X_i)$ *are asymptotically independent. Furthermore, as* $n \to \infty$, *the random variable* q_{un} is asymptotically gamma distributed, that is,

$$nq_{u_n} \xrightarrow{L} \Gamma \tag{10}$$

where Γ *is a gamma (2,1) random variable.*

In particular, the GEV-fitted data can be transformed into unit Fréchet scales (Pickands III, 1975; Embrechts et al., 1997; Smith, 2003), and then the TQCC can be calculated by using the estimated GEV parameters (Zhang et al., 2017). In this paper, since the domain of attraction of all variables are Type II GEV (Fréchet), we fit each monthly maxima sequence with AcF(1,1) model and yield dynamic Fréchet parameters. Based on that, we can obtain the recovered Fréchet sequences of all variables and use them for the TQCC computation. In addition, by using the rolling window method, time-varying TQCC can be estimated for investigating the dynamic tail spillover effects (see Section 5.3).

There are merits for using the GEV-AcF-TQCC framework in the tail risk spillovers study. First, TQCC outperforms other approaches in terms of accuracy, robustness, and universality. The TQCC can measure global tail correlations, which cannot be achieved using classical methods such as copula. The reason is that the traditional approaches are model-based methods that require the joint modeling of variables. However, in reality, the dependencies across sections often change over time. The underlying model needs to be modified when dependencies vary, making it challenging to specify an appropriate dependence model. In contrast, TQCC does not require any pre-assumptions of cross-sectional dependence structure, thereby bringing more modeling accuracy and robustness. It has been tested by Zhang (2008) that TQCC outperforms Gumbel copula and many other conventional methods. Second, given that first point, the calculation of TQCC is of simplicity, that is, as simple as the computation of sample Pearson's linear correlation coefficient. Third, TQCC can directly evaluate the correlation between block maxima, which cannot be fulfilled by using traditional Pearson's linear correlation coefficient or other Gaussian-based models (Zhang, 2008).[1] These observations form the rationale of using the GEV-AcF-TQCC method in this paper, as the variables of interest in this study are all monthly block maxima. Last but not least, rolling window TQCC is a natural modeling idea to illustrate the dynamics of extreme co-movements (see Section 5.3). However, if traditional methods like Gumbel copula are applied, investigating dynamic spillovers can be extremely difficult because the underlying (static) model may not be the same over time.

4. Variables and data

This study utilizes two categories of data: Infectious Disease Equity Market Volatility Tracker and crude oil futures prices. All original data are daily data, and we take monthly maximum values for each variable for modeling the extremes. Detailed variable descriptions are shown in Table 1. According to Section 5.1, the shape parameters of all variables are positive, meaning that the domains of attraction of these variables are Type II GEV, i.e., the Fréchet distribution.

Baker et al. (2020) constructed a newspaper-based Infectious Disease Equity Market Volatility (EMV) Tracker, counted across approximately 3000 newspapers. This daily measure is available from January 1985 to the present and is updated daily at http://www.policyuncertainty.com/infectious_EMV.html. In this study, we use the daily data from March 1, 2002, to September 30, 2021, and convert them into monthly maxima. See Fig. 1 for the histogram display of the monthly maxima data. During the sample period, there are three clustering periods of the infectious disease EMV monthly maxima: (1) from September 2008 to January 2009, (2) from November 2014 to January 2015, and (3) from January 2020 to Sep 2021 (the end of sample period of this study). These three infectious diseases' EMV maxima periods correspond to Avian flu (2007–2009), Ebola virus (2014–2015), and COVID-19.

The crude oil futures data are extracted from the Investing database (investing.com), and the daily data are used to convert to monthly maxima. We investigate both the upside and downside extreme movements of Brent and WTI crude oil futures. We use the monthly block maxima of daily returns and negative daily losses for modeling the upside and downside extreme movements, respectively. Except for WTI crude oil futures on April 20, 2020, all daily returns are calculated on logarithmic returns. On April 20, 2020, WTI crude oil futures showed a negative price, and we replaced the logarithmic return with a simple return.

Table 2 reports the descriptive statistics for all variables. The mean values of WTI are larger than those of Brent for both downside and upside, meaning that the WTI market generally fluctuates more severely than the Brent market. The maximum of WTI (down) is 3.060, far more than other variables due to the "negative price" event" on April 20, 2020. The kurtosis and skewness of each crude oil market variable and the infectious disease variable are greatly larger than 3 and 0, respectively. These facts strongly imply that the variables of interest are highly asymmetrically distributed. Besides, the Jarque-Bera (J-B) tests are conducted for both the original sample and block maxima of all variables. All the resulting J-B stats (H-values) are 1 with a p-value equaling to 0, meaning that all the null hypotheses of normality are rejected at 0.01 level, and both the original sample and monthly block maxima sequences are not normally distributed.

Fig. 2 displays the time series sequences of the crude oil futures. As shown, for both Brent and WTI, the downside and upside movements are time-varying, asymmetric, share similar patterns. It is worth noting that there are three periods when the movements in both sides are extremely large: (1) from Nov 2008 to May 2009; (2) from Jan 2015 to Dec 2015; and (3) from Apr 2020 to July 2020. Among all the above periods, the one from Apr 2020 to July 2020 is the most severe one, which entails the "negative price" event of WTI. Upon that event, the downside movement of WTI (silver line) is as large as more than 3.

5. Empirical results

5.1. The GEV estimations

Table 3 provides the GEV estimation results of all variables. As shown, the shape parameter (tail parameter) ξ is positive for each variable, which means all variables follow the Type II GEV (Fréchet) distribution, and there are no upper bounds for all the variables. The positive shape parameters also indicate that the underlying distributions of these variables are all asymmetric and have infinite tails. For example, the shape parameter of infectious disease (ID) is greater than 0.8, which indicates that the scale of a "rare" infectious diseases event can be extremely huge and thus cannot be ignored. For both directions, the tail parameters of Brent and WTI are greater than 0.15 and 0.20, respectively. This means that the underlying distributions of crude oil futures returns and losses are highly asymmetric and have "fat tails."

[1] According to Zhang et al. (2011), the sample-based Pearson's linear correlation coefficient and the quotient correlation coefficient are asymptotically independent.

Table 1
Descriptions of the monthly block maxima variables and data.

Variables	Definition	Domain of attraction
Infectious disease EMV (ID)	The monthly maxima of daily Infectious Disease Equity Market Volatility Tracker	Type II GEV (Fréchet)
Brent crude oil downside movement (Brent (down))	The monthly maxima of daily Brent crude oil futures negative losses	Type II GEV (Fréchet)
Brent crude oil upside movement (Brent (up))	The monthly maxima of daily Brent crude oil futures returns	Type II GEV (Fréchet)
WTI crude oil downside movement (WTI (down))	The monthly maxima of daily WTI crude oil futures negative losses	Type II GEV (Fréchet)
WTI crude oil upside movement (WTI (up))	The monthly maxima of daily WTI crude oil futures returns	Type II GEV (Fréchet)

Note: This table describes the variables and data utilized in this paper. The original daily data is from March 1, 2002, to September 30, 2021. The Infectious Disease Equity Market Volatility Tracker is proposed by Baker et al. (2020), and its data is from http://www.policyuncertainty.com/infectious_EMV.html. The data of crude oil futures are from Investing database (http://investing.com).

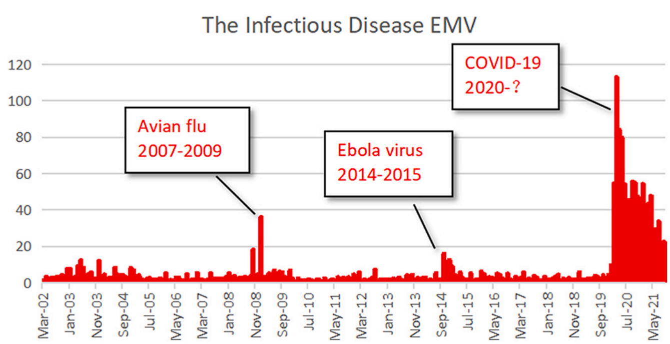

Fig. 1. The histogram display of the monthly maxima infectious disease EMV. Note: This figure shows the bar chart of Infectious Disease EMV from May 2020 to Sep 2021. There are three notable large values clustering periods: (1) from September 2008 to January 2009, (2) from November 2014 to January 2015, and (3) from January 2020 to Sep 2021 (the end of sample period of this study). These three infectious diseases' EMV maxima periods correspond to Avian flu (2007–2009), Ebola virus (2014–2015), and COVID-19.

Meanwhile, the shape parameters of WTI are larger than those of Brent in both directions, meaning that WTI has "fatter" tails on both sides than Brent and is, therefore, more vulnerable to tail risks from both directions than Brent.[2]

5.2. The AcF model estimations and tail indexes

Table 4 lists the AcF (1,1) model estimation results.[3] Fig. 3 (a) shows the AcF model-based tail index estimation of the infectious disease. It can be found from the figure that the tail index of infectious disease EMV is usually above 2.30, except for three time periods: (1) from Nov 2008 to Feb 2009; (2) from Nov 2014 to Feb 2015; and (3) from Feb 2020 to Sep 2021 (the end of the sample period of this study). These three time periods correspond to extreme infectious public health events: Avian flu from 2008 to 2009, Ebola from 2014 to 2015, and COVID-19 after Jan 2020. This means that 2.30 can be regarded as an empirical threshold to distinguish if there is an extremely infectious disease event. Intuitively, since the AcF tail index is the shape parameter of the underlying distribution, a slightly marginal change in the tail index implies a huge and abrupt movement in the monthly block maxima. In this regard, the AcF tail index can also be called the "super volatility."

The dynamic AcF model-based volatility estimation result is displayed in Fig. 3(b), which provides additional information to Fig. 3(a). As shown in Fig. 3(b), there are three periods when the AcF volatility surpasses 2, which happen to be the periods of three infectious public health extreme events. In addition, one can significantly distinguish the period of COVID-19 from the other two by judging from the volatility values. It is too notable for ignoring that the AcF volatility of infectious disease EMV ranges from 15 to (more than) 65 during the COVID-19, while the volatilities are no more than 10 during the Avian and Ebola periods.

Integrating the above empirical findings, we conclude that: (1) when an extreme event occurs, the AcF tail index of infectious disease EMV reaches its lower empirical threshold, which is about 2.30; and (2) only when the tail index reaches its empirical lower bound which implies an extreme situation, the AcF volatility significantly jump up.

The above findings have at least two economic meanings. First, one can distinguish extreme circumstances from normal situations by examining the value of the AcF tail index of infectious disease EMV. For example, an extremely infectious disease event might occur if the empirical AcF tail index value goes down to about 2.30. In other words, the tail index may serve as a leading indicator for infectious disease warnings. Consequently, government officials may act in advance for epidemic prevention and control, and investors may do marketing timing based on this signal (see Section 7 for detailed policy implications). Second, in extreme circumstances like COVID-19, one can tend to the AcF volatility of infectious disease EMV for additional information regarding the dynamic severeness of the epidemic.[4]

Fig. 4 shows the AcF(1,1) model-based tail indexes estimations for the oil futures. As shown, except for Brent (down), which typically fluctuates between [5,20], the typical range for tail indexes of crude oil futures is [2,10], and the tail risks of oil futures prices are time-varying. These findings present evidence of skewed behaviors of both upside and downside movements. The tail indexes show a consistent trend, indicating that the tail risks in crude oil markets are simultaneous and bi-directional. It is interesting to see that there are varies "empirical thresholds" for the extreme movements: for the Brent oil, the downside tail index is usually greater than 6, and the upside is generally above 4; and for the WTI, the tail indexes for downside and upside movements are seldom going below 4 and 3, respectively. Meanwhile, the tail indexes of the downside are relatively lower than that of upside for both Brent and WTI, suggesting that the left tails are heavier than the right tails. According to Fig. 4, there are three time periods when the AcF tail indexes of all crude oil futures go below their "extreme events" thresholds: (1) from Nov 2008 to May 2009; (2) from Jan 2015 to Dec 2015; (3) from Apr 2020 to July 2020. In these periods, each tail index reached a trough, which means that the asymmetry of the distribution is extremely severe, and tail risks are particularly high.

Fig. 5 displays the resulting AcF(1,1) model-based volatilities. As shown, the AcF volatilities are all time-varying and share the same pattern. However, there are three periods that the volatilities jump to relatively higher levels: (1) from Nov 2008 to May 2009; (2) from Jan

[2] This result is consistent with the facts in April 2020 when crude oil markets crashed. In that extreme event, the price of the main WTI contract fell below zero, and all Brent contrasts prices were still positive.

[3] In this study, we choose the burn-in period to be 50 observations, which means that 50 more observations before the start date of the sample period have been included in the time series model estimation so as to ensure the robustness of our results. Note that these 50 observations are only used in the computation of Table 4, i.e., not for the remaining computations. We also tried several different starting time points, seeds, and burn-in numbers when doing this research, and the major findings remained stable. These results can be obtained upon request to the authors.

[4] As can be seen from Fig. 3 (b), after the COVID-19 vaccine came out and people around the world were vaccinated in the first half of 2021, the volatility significantly decreased.

Table 2
The descriptive statistics for the monthly block maxima variables.

Variable	Obs	Mean	Std. Dev.	kurtosis	skewness	Min	Max
ID	235	7.269	14.778	20.477	3.919	0.590	112.930
Brent (down)	235	0.017	0.013	39.260	4.931	0.003	0.121
Brent (up)	235	0.018	0.010	12.793	2.557	0.004	0.083
WTI (down)	235	0.031	0.199	231.502	15.158	0.004	3.060
WTI (up)	235	0.019	0.014	28.932	4.243	0.005	0.139

Note: This table shows the descriptive statistics for the block maxima variables. The kurtosis and skewness of each variable are far more than 3 and 0, respectively. This means that the variables of interest are highly asymmetrically distributed, consistent with the results of the J-B tests.

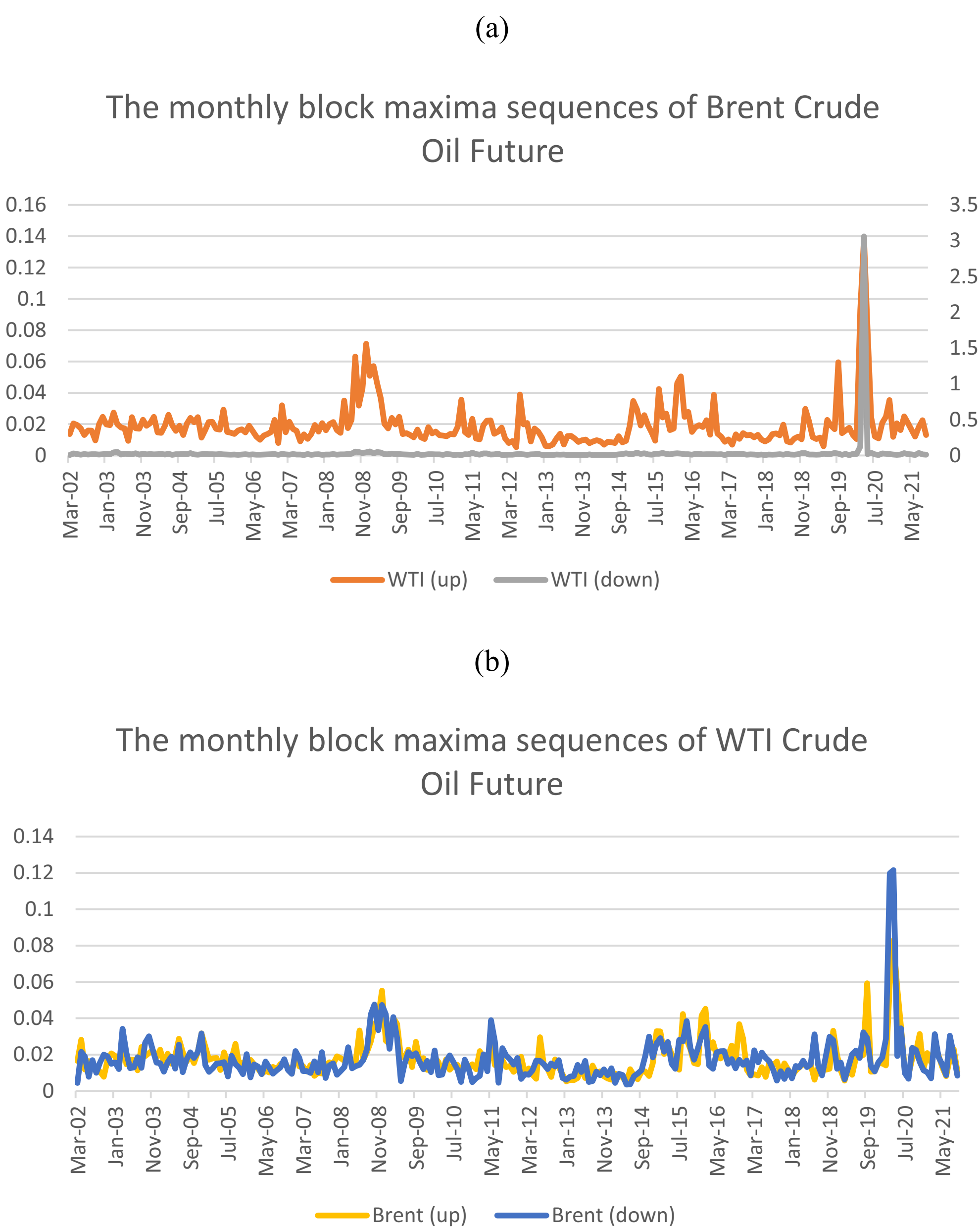

Fig. 2. The line curves for (a) Brent crude oil futures; (b) WTI crude oil futures.
Note: This figure displays the time series sequences of the monthly block maxima sequences of Brent and WTI crude oil futures in panels (a) and (b), respectively. In panel (a), the scale of upside movement (orange line) is marked on the left axis, and the scale of downside movement (silver line) is marked on the right axis. For example, upon the "negative price" event of WTI on April 2020, the downside movement of WTI (silver line) is as large as more than 3.

2015 to Dec 2015; (3) from Apr 2020 to July 2020, corresponding to the three periods that the AcF tail index of infectious disease EMV reached its empirical lower bound, 2.30. This means that in extreme circumstances, the volatility of crude oil futures does go up, which is in line with the empirical findings in the literature (see Huang et al., 2019; Okorie and Lin, 2020; Gil-Alana and Monge, 2020). Specifically, in April 2020, the volatility of WTI (down) jumps to a value larger than 0.20, which is much greater than its normal value, corresponding to the "negative price" event.

5.3. *The TQCC estimations and tail risk spillover effects*

This subsection aims to answer two questions: First, can extreme events of infectious diseases lead to severe fluctuations in the crude oil

Table 3
The GEV estimations for the monthly block maxima variables.

	ξ	σ	μ
ID	0.8115 (0.0666)	1.4655 (0.1266)	2.0507 (0.1049)
Brent (down)	0.1563 (0.0445)	0.0062 (0.0003)	0.0126 (0.0004)
Brent (up)	0.1960 (0.0533)	0.0058 (0.0002)	0.0130 (0.0004)
WTI (down)	0.2889 (0.0462)	0.0065 (0.0003)	0.0134 (0.0005)
WTI (up)	0.2069 (0.0435)	0.0058 (0.0003)	0.0137 (0.0004)

Note: This table displays the GEV estimation results for the monthly block maxima. The scale, shape, and location parameters are shown in the first, second, and third columns. The estimated standard deviations are listed in parentheses. As shown, all parameters are significant, as their estimated values are twice greater than the corresponding standard deviations. In this table, the decimal points are kept to the 4th place for the detailed illustration of the values of location parameters and standard deviations. For example, if only 3 decimal points are kept, three location parameters would be displayed as 0.013, which may miss useful information.

market? Second, does the dynamic tail dependence between infectious diseases and crude oil futures markets before crises share some common patterns?

The first question is a static problem. Regarding this question, we use TQCC to measure the tail dependence between infectious diseases and extreme movements of the crude oil futures. Theoretically, the larger the TQCC, the more severe the tail dependence. In this study, the random threshold is taken as the larger one of each sequence's upper 5% quantile. The full sample TQCC estimation results are shown in Table 5.

The second question is a dynamic problem. Regarding this question, we firstly fit the AcF(1,1) model and then insert the resulting AcF parameters into the TQCC algorithm via rolling windows. Each dynamic TQCC is calculated using 36, 48, and 60 observations of the most recent period, that is, 3-year, 4-year, and 5-year rolling windows are used. The dynamic TQCC results are shown in Fig. 6.

Table 5 shows the full sample TQCC estimation, which measures the degree of tail dependent or to what extent a crude oil future variable co-moves with infectious disease and other variables. Using 0.393 (the TQCC value for WTI (up) and ID) as an example, it means there is a 39.3% chance that given the infectious disease reaches an extremely high level, the upside movement of WTI futures price reaches its extremely high level at the same time. Other TQCC values are interpreted similarly.

Table 5 evidences that (1) all tail correlation coefficients are significant at the 0.01 level, which means that the extreme co-movements between infectious disease and extreme movements of crude oil futures on both sides are significant; and (2) the static TQCC values are different in upside and downside, meaning that the extreme co-movements are asymmetric. Specifically, the static TQCC of each upside movement is greater than the corresponding downside, which means that extreme infectious disease events are more likely to lead to sudden skyrockets rather than abrupt plunges in crude oil prices. Nevertheless, this does not mean that the downside co-movements are so weak that they can be ignored. For example, the TQCC between WTI (down) and ID is 0.122, which intuitively means that there is more than 10% chance that the WTI future may fall extremely sharply once extreme pandemics break out. Furthermore, one needs to further investigate the dynamic TQCC structure for detailed information at a given time point. For instance, the dynamic TQCC values between WTI (down) and ID were as large as 0.70 or even more before the "negative price" event in April 2020 (see Fig. 6).

The existence of bi-directional extreme co-movements can be intuitively interpreted for the following two reasons. First, as an extreme public health event sweeping the world, infectious diseases like COVID-19 can simultaneously impact both the buy and sell sides of crude oils, resulting in extreme fluctuation in both directions. Second, futures prices may "backfire" after a single directional extreme movement, thereby causing (asymmetric) movements on the opposite side. The rationale of the backfiring effect is the "market failure" in an extreme situation because of the uncertainty and market tension resulting from the extreme event and the lack of market liquidity. Consequently, an asset can be overpriced (underpriced) after a large one-day surge (pump) for several days. However, when market sentiments alleviate, and liquidity goes sufficient, the mispricing phenomena will be removed. This is the reason why a sharp fall (a sharp rise) is usually followed by another fierce backfiring rise (fall) during an extreme event. Meanwhile, since the degrees of price fluctuations for an extreme event and its backfiring effect may not be exactly the same, the co-movements in upside and downside are asymmetric. To sum up, extreme co-movements between infectious disease and crude oil futures are bi-directional and asymmetrical. These findings are consistent with the results of Shahzad et al. (2018).

Specifically, the downside co-movements revealed in Table 5 can be interpreted in a naive supply-demand economic framework. The global spread of extremely infectious diseases may reduce production globally, reducing the demand for energy, including crude oil (Qin et al., 2020). However, since it takes time for energy suppliers to adjust their production strategy, it is hard to suddenly reduce production and sell the existing inventory. The co-movement of the COVID-19 and the "negative price" of WTI is a good example at this point. Due to the epidemic, many factories have to shut down in the first quarter of 2020, which led to an instantaneous reduction in energy demand, resulting in excess energy production capacity and a sharp drop in crude oil futures prices. When the costs of transportation, storage, and disposal services of WTI crude oil exceed the commodity prices, the future price eventually goes below zero.[5] In addition, geopolitical issues also lead to sudden changes in supply and demand structure (see Section 6 for further discussion).

Fig. 6 provides evidence of the dynamic tail risk spillovers patterns between infectious diseases and crude oil futures. The robustness of the dynamic tail contagions results can be demonstrated in the following two empirical facts: (1) the dynamic TQCCs have similar patterns under 3-, 4-, and 5-year rolling windows; and (2) all TQCCs series have consistent trends before the oil futures market skyrocketed or plummeted.

The main findings of Fig. 6 can be summarized as follows. First, in the "quiet period" when there are no extremely large returns or losses in the crude oil futures market, the overall levels of TQCCs are different, and there are no common patterns in their trends. Second, each TQCC typically reached a relatively higher level before and during an extremely infectious disease event and then dropped abruptly after the extreme infectious disease event. Specifically: (1) during the Avian flu period, all TQCCs fell from September to November 2008, which predated the outbreak of extreme tail risks in the crude oil futures market in November 2008; (2) during the Ebola virus period, all TQCCs fell from September to November 2014, which predated the outbreak of extreme tail risks in the crude oil futures market in November 2014; and (3) regarding the most recent COVID-19, all TQCCs started to fall in February 2020, and the oil futures market crashed in April 2020, which includes the "negative price" event.

The above findings provide evidence for the tail risk spillovers from infectious disease to crude oil futures markets. When extreme infectious disease events broke out in the sample period, each TQCC increased to a relatively higher level. Subsequently, crude oil market prices fluctuated sharply, and then TQCCs went down quickly. Given this fact, we can regard the TQCC between infectious diseases and crude oil futures markets as the "factor loading" of infectious diseases tail risks in the crude oil market. When TQCC rises, systemic risks of infectious diseases begin to accumulate in the crude oil futures market. When TQCC reaches a relatively high level compared with the past period, it shows that the systemic risk from infectious diseases has passed to the crude oil futures

[5] Of course, the geopolitical issue between the Russia and OPEC also contributed to the "negative price" event.

Table 4
The estimated AcF (1,1) parameters.

	γ_0	γ_1	γ_2	γ_3	β_0	β_1	β_2	β_3	μ
ID	0.830 (0.410)	0.001 (0.487)	1.302 (1.380)	1.172 (1.015)	2.200 (0.098)	0.630 (0.014)	−1.950 (0.113)	0.018 (0.002)	−0.676 (0.440)
Brent (down)	−0.376 (0.599)	0.424 (0.150)	2.313 (0.744)	12.996 (5.259)	−1.073 (0.297)	0.552 (0.112)	−0.140 (0.079)	43.692 (32.250)	−0.065 (0.037)
Brent (up)	−97.677 (2.207)	0.492 (0.004)	98.736 (2.197)	0.126 (0.046)	−2.210 (0.404)	0.312 (0.098)	−0.730 (0.237)	48.454 (20.428)	−0.011 (0.007)
WTI (down)	−1.098 (1.074)	0.001 (0.190)	3.297 (0.976)	7.391 (4.166)	−0.945 (0.713)	0.216 (0.077)	−1.867 (0.782)	5.738 (2.971)	−0.021 (0.010)
WTI (up)	−56.338 (1.160)	0.571 (0.003)	56.976 (1.169)	0.0950 (0.045)	−1.795 (0.323)	0.403 (0.088)	−1.073 (0.233)	29.412 (11.202)	−0.003 (0.003)

Note: This table provides the parameter estimation results of the AcF (1,1) model. The estimated standard deviations are listed in parentheses. We note that some estimations are insignificant in this table, likely because the lengths of time series are not long enough. However, considering the AcF structures and the comparisons among all variables, we keep the estimated models for further analysis and inference. The models can be updated when more data are collected.

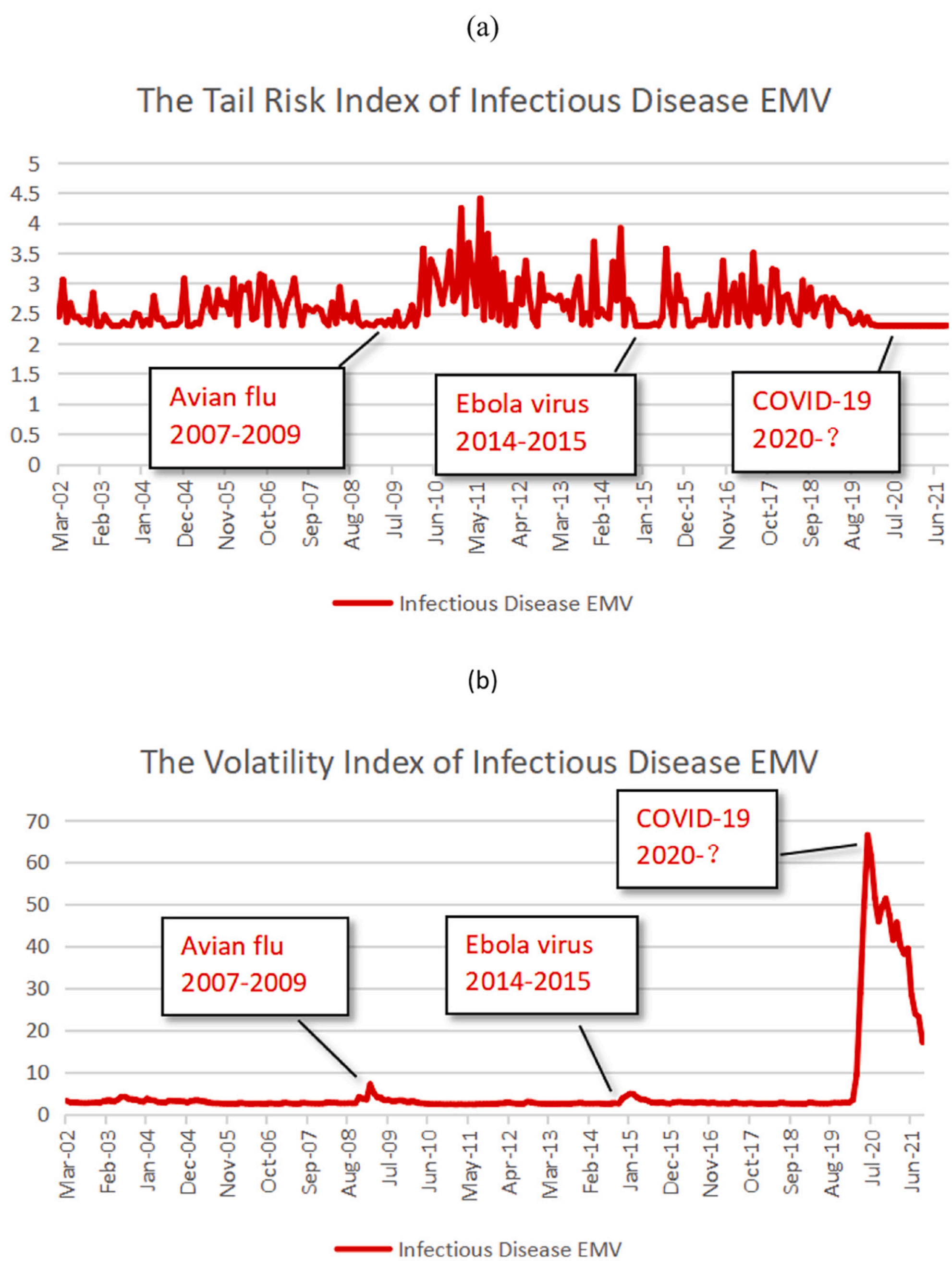

Fig. 3. (a) The AcF tail index estimation of the infectious disease EMV; (b) The AcF volatility estimation of the infectious disease EMV.
Note: This figure shows the AcF model-based tail index and volatility dynamics of the Infectious Disease EMV in panels (a) and (b), respectively. In panel (a), the tail index of Infectious Disease EMV is usually above 2.30, except for three time periods: (1) from Nov 2008 to Feb 2009; (2) from Nov 2014 to Feb 2015; and (3) from Feb 2020 to Sep 2021 (the end of the sample period of this study). These three time periods correspond to extreme infectious public health events: Avian flu from 2008 to 2009, Ebola from 2014 to 2015, and COVID-19 after Jan 2020. In panel (b), there are three periods when the AcF volatility surpasses 2, which happen to be the periods of three infectious public health extreme events.

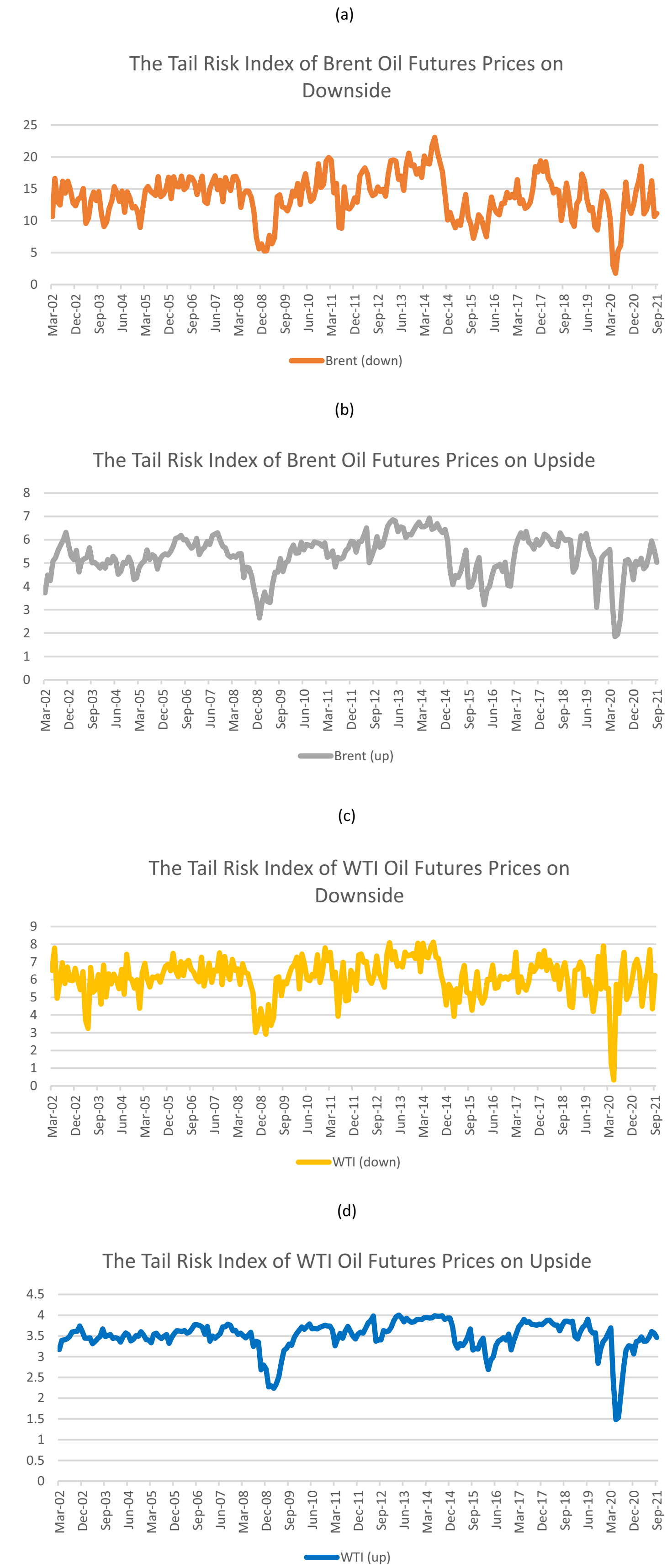

Fig. 4. The AcF tail indexes estimations of: (a) Brent Oil downside; (b) Brent Oil upside; (c) WTI Oil downside; (d) WTI Oil upside.
Note: This figure shows the AcF model-based tail index dynamics of Brent and WTI crude oil futures. As shown, except for Brent (down), which typically fluctuates between [5,20], the typical range for tail indexes of crude oil futures is [2,10].

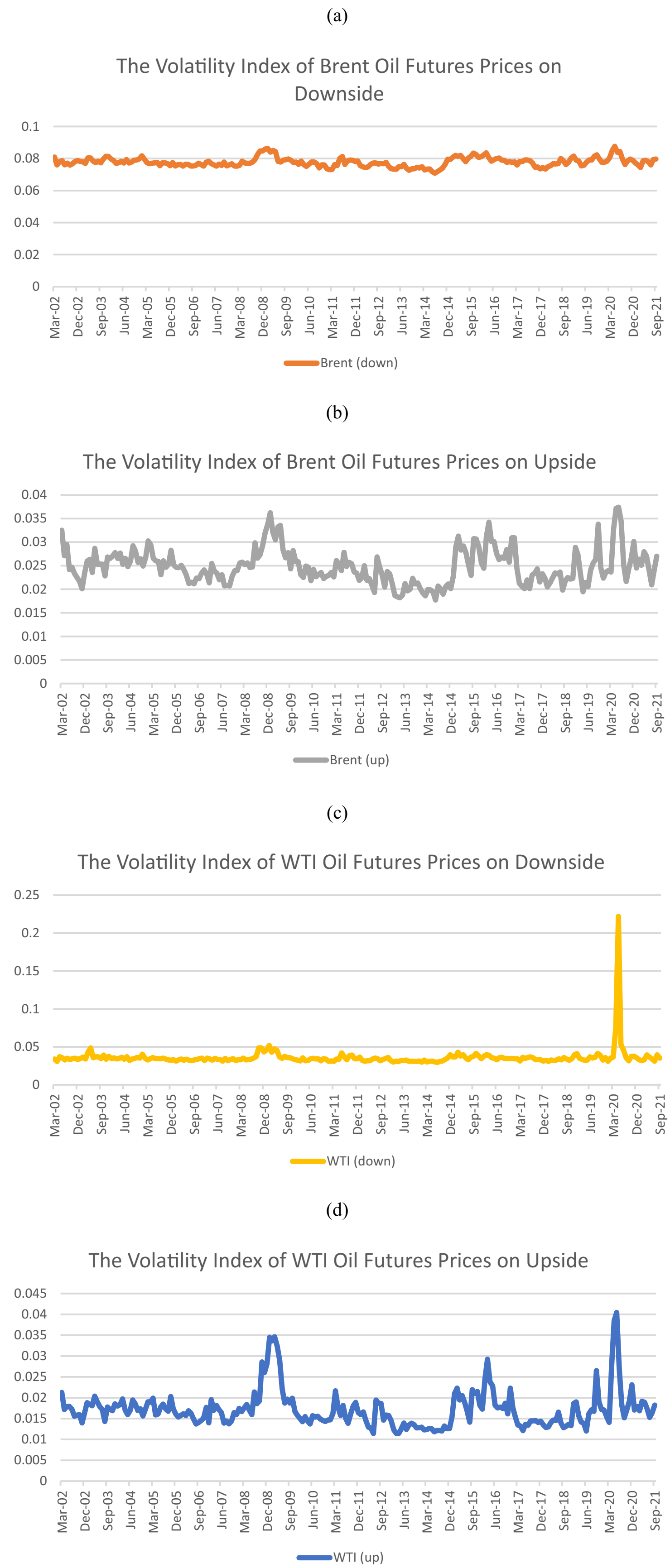

Fig. 5. The AcF volatilities estimations of (a) Brent Oil downside; (b) Brent Oil upside; (c) WTI Oil downside; (d) WTI Oil upside.
Note: This figure shows the AcF model-based Brent and WTI crude oil futures volatility dynamics. As shown, there are three periods that the volatilities jump to relatively higher levels: (1) from Nov 2008 to May 2009; (2) from Jan 2015 to Dec 2015; (3) from Apr 2020 to July 2020.

Table 5
The full sample TQCC estimations of monthly block maxima.

	ID	Brent (down)	Brent (up)	WTI (down)
Brent (down)	0.164***			
Brent (up)	0.376***	0.139***		
WTI (down)	0.122***	0.149***	0.092***	
WTI (up)	0.393***	0.158***	0.562***	0.069***

Note: This table displays the resulting TQCC values of all block maxima pairs. *** means the p-value is less than 0.001.

market, and a sharp rise or plunge is about to come. Conversely, after reaching a relatively higher level, each TQCC dropped down suddenly and sharply, indicating that the tail risk began to "release" in the crude oil futures markets. This could soon be reflected in asset prices by skyrocketing (if demand exceeds supply) or plummeting (if supply exceeds demand). Therefore, a sudden decline of the TQCC from a high level may signal an upcoming skyrocket or crash in crude oil futures markets, which may offer implications for investors and policymakers. In practice, one can refer to the dynamic TQCC values and the proposed GEV-AcF-TQCC framework for market timing and tail risk warning (see Section 7).

6. Discussions

Regarding the empirical findings of this paper, we explain the economic mechanism of the influence of infectious disease events on crude oil futures prices from the following three possible channels (financial mechanism, macroeconomic policy mechanism, and geopolitical mechanism), which may provide motivations for future empirical study.[6]

The first channel is the tail risk premium channel. The extreme shocks resulting from infectious disease constitute the tail and systemic risks. As a result, extreme infectious disease events can increase the risk premium and be reflected in asset prices. Therefore, an extreme event can be seen as an individual tail risk factor. Given the "risk-averse" setting of investors, which is a common pre-assumption in financial literature, it is natural to believe that investors are also "tail risk-averse" when facing extreme events, and each tail risk factor is supposed to be priced.

The second channel is the policy-liquidity channel. Extreme events, such as global infectious diseases, may drive the government and central bank to adjust policies, especially monetary policy, which can profoundly affect market liquidity and further affect asset prices. Policy responses may not only help reduce the spread of infectious disease per se but also moderate its negative impact on industrial productivity and steer countries back to their growth paths (Iyke et al., 2021). Given this argument, it can be of practical significance to determine how the monetary policies are supposed to respond to infectious disease and other tail risk factors via the market liquidity channel.

The third channel can be the geopolitics-supply-demand channel. The spread of the virus may affect geopolitics and inter-state games, thereby changing the global energy supply-demand structure and impacting crude oil prices. For example, the outbreak of COVID-19 in early 2020 caused severe overcapacity in many countries and led to subtle changes in the geopolitical landscape. Russia and OPEC thus began a "price war" (Ozili and Arun, 2020; Poitiers and Domínguez, 2020), which was the fuse for the price collapse of crude oil futures in early 2020 and the reason why the main WTI crude oil futures contract rarely reached "negative prices" in April 2020.

[6] We note that the economic channels are from infectious diseases to crude oil futures markets, but not reversely. A fact supporting such a statement is that the monthly maxima of the ID EMV almost always precede that of crude oil futures. For example, the "negative price" extreme event of WTI was on 20 April 2020, while the maxima of ID EMV (84.08) of that month was on 5 April 2020.

Regarding the above channels, in the future, it would be of both academic and practical significance (1) for financial researchers to investigate how tail risk factors like infectious disease add to tail risk premia on financial assets, (2) for macroeconomic and monetary economists to study that how extreme infectious disease events affect assets prices via market liquidity, and (3) for scholars in political economics and geopolitical realms to figure out how infectious diseases affect geopolitics and inter-state games, thereby changing global energy supply-demand structure.

7. Conclusions and implications

This paper examines the extreme co-movements between infectious disease events and crude oil futures markets using the GEV-AcF-TQCC framework. By fitting the block maxima variables with generalized extreme value (GEV) distribution, the Autoregressive conditional Fréchet (AcF) model and the tail quotient correlation coefficient (TQCC) are further used to study the static and dynamic extreme co-movements and tail risk spillovers between infectious diseases and crude oil futures markets. The major findings are as follows: (1) the domains of attraction of infectious disease and crude oil futures are Type II GEV, meaning that there are no upper bounds for their maxima; (2) extreme co-movements of infectious disease and crude oil futures are found in both sides whereas they are asymmetric; (3) when an extreme event occurs, the AcF tail index of infectious disease EMV reaches its lower empirical threshold which is about 2.30; (4) when a jump in volatility corresponding to the severeness of the pandemic is observed, the tail index reaches the lower bound, but not reversely; (5) the full sample gamma test shows that TQCCs between infectious disease cases and crude oil futures prices are statistically significant; and (6) the rolling window TQCC shows that tail dependence between crude oil futures prices and infectious disease events may keep rising and reach relatively higher levels before crises, and fall sharply with the collapse of the crude oil futures markets.

Our findings may offer novel and interesting implications for government officials, financial investors, portfolio managers, and policymakers.

First, government officials, epidemic prevention and control personnel, and epidemiological researchers may act in advance for epidemic prevention and control by tracing the infectious disease AcF tail index and AcF volatility. As shown in Fig. 3 and explained in Section 5.2, the AcF tail index can be used as a leading indicator for infectious disease warning, and the AcF volatility may provide additional information for pandemic severeness when in an extreme period. In practice, if the AcF tail index jumps down to about 2.30, which is the empirical threshold for "extreme pandemic events," this might be a strong signal for government officials and epidemic prevention and control workers to improve vigilance against the spread of the virus and adjust their deployment of epidemic prevention and control.

Second, our findings may provide information for financial investors for their market timing. By looking at the AcF tail index of infectious disease, investors can distinguish the "extreme time" from the "normal period," thereby seeking market opportunities in an upcoming "extreme event." In addition, the discovery of tail risk factors and early warning of tail risk provide speculators with the possibility to speculate at a low cost (Bhansali, 2015). In practice, investors can choose the timing of tail speculation by calculating the TQCC of infectious disease EMV and crude oil futures. When TQCC sequences peaked and suddenly fell, this may herald a tail speculation opportunity in the crude oil market.

Third, our findings and the proposed GEV-AcF-TQCC framework for portfolio managers may imply possible solutions for their tail risk hedging problems. For example, as shown in Table 5, the TQCC between Brent (down) and WTI (down) is 0.149, and the TQCC between Brent (up) and WTI (up) is 0.562. Thus, using the short position of one crude oil future to hedge the long position of the other crude oil can be a natural and practical way for tail risk hedging. In addition, using the

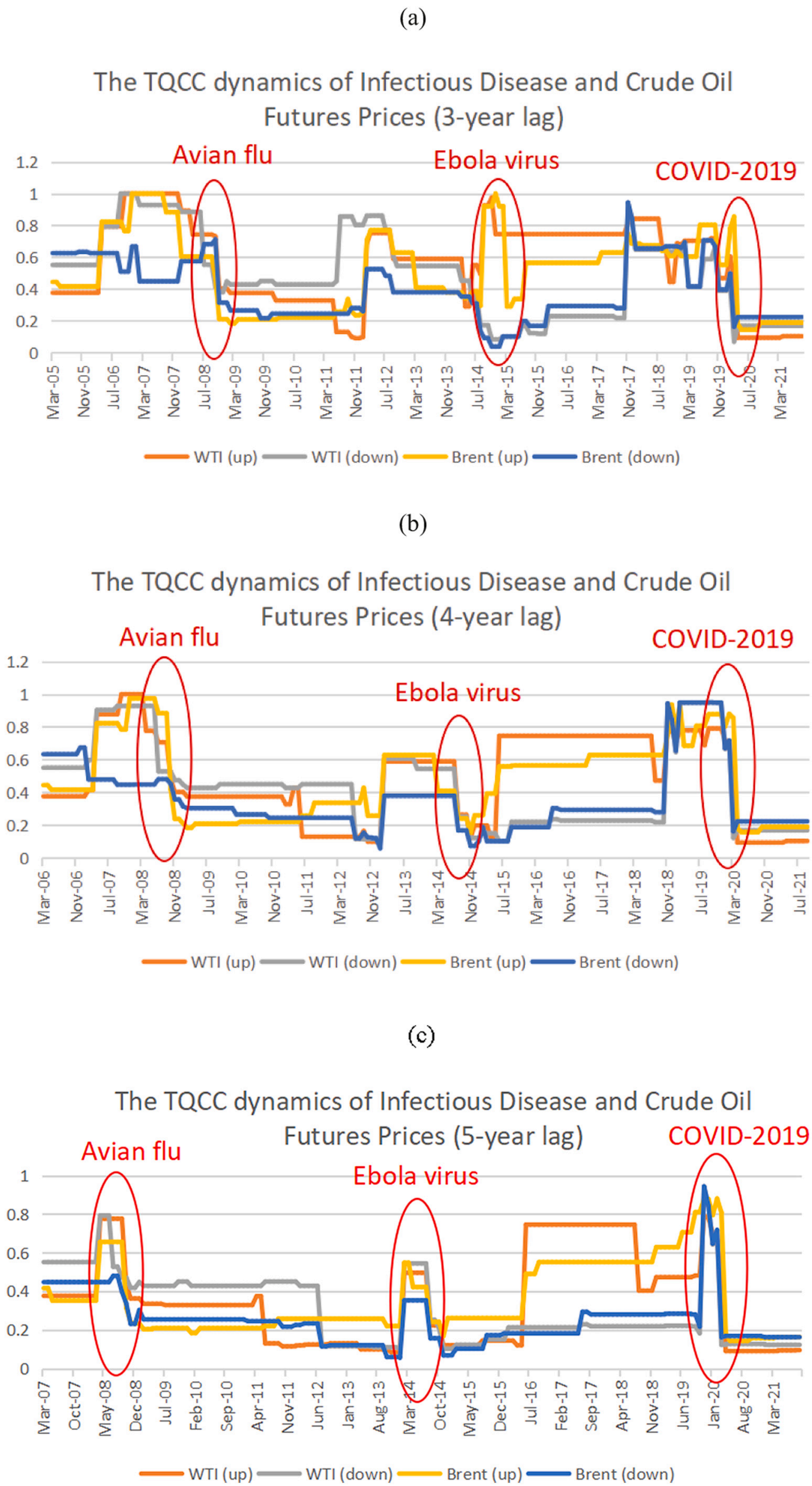

Fig. 6. The TQCC dynamics of Infectious Disease and Crude Oil Futures Prices using: (a) 3-year rolling window; (b) 4-year rolling window; (c) 5-year rolling window.

Note: This figure displays the dynamic TQCC results using the rolling window period of 3, 4, and 5 years in panels (a), (b), and (c), respectively. The TQCC patterns are almost the same in all panels, which demonstrates the robustness of the results. As shown, each tail quotient correlation coefficient keeps rising and reaches a peak before crises and falls sharply with the collapse of crude oil markets.

GEV-AcF-TQCC framework, one can further investigate how to hedge the infectious disease tail risk in crude oil futures markets using other assets. Co-movements between crude oil futures and other assets certainly need to be considered to fulfill this task. See Feng et al. (2018), Pal and Mitra (2019), and Okorie and Lin (2020) for more details in this regard.

Finally, macroeconomic policymakers might be inspired by the empirical evidence of the TQCC pattern before and after pandemics, thereby contributing to their policy formulation. The fact that higher extreme co-movements and tail spillovers occurred just before crisis periods makes it possible for policymakers to warn of crises in the crude oil futures market and adopts industrial policy (in terms of long-run) and monetary policy (in terms of short-run) tools to hedge the tail risks caused by infectious diseases in macroeconomic level. In practice, to respond to market panic expectations under extreme events, forward-looking monetary policy can be adopted, such as quantitative easing and expanding the acceptance of collateral (the "haircut") in the inter-bank market (Nyborg, 2017; Prorokowski et al., 2020).

CRediT authorship contribution statement

Hang Lin: Conceptualization, Software, Validation, Formal analysis, Data curation, Writing – original draft, Writing – review & editing, Visualization. **Zhengjun Zhang:** Conceptualization, Methodology, Validation, Writing – original draft, Writing – review & editing, Supervision, Project administration.

Acknowledgements

The authors thank the editor Prof. Paresh Narayan and four anonymous reviewers for their insightful comments, which help improve the quality of the paper. In addition, Zhengjun Zhang is grateful for the support from NSF grant (Number: NSF-DMS-2012298). Finally, the paper's views are sole of the authors and not necessarily of NSF.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.eneco.2022.106054.

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