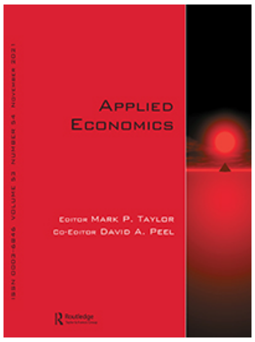

Applied Economics

ISSN: (Print) (Online) Journal homepage: https://www.tandfonline.com/loi/raec20

Financial contagion among COVID-19 concept-related stocks in China

Shaen Corbet, Yang (Greg) Hou, Yang Hu & Les Oxley

To cite this article: Shaen Corbet, Yang (Greg) Hou, Yang Hu & Les Oxley (2021): Financial contagion among COVID-19 concept-related stocks in China, Applied Economics, DOI: 10.1080/00036846.2021.1990844

To link to this article: https://doi.org/10.1080/00036846.2021.1990844

Published online: 18 Oct 2021.

APPLIED ECONOMICS
https://doi.org/10.1080/00036846.2021.1990844

Financial contagion among COVID-19 concept-related stocks in China

Shaen Corbet[a,b], Yang (Greg) Hou[a], Yang Hu[a] and Les Oxley[a]

[a]School of Accounting, Finance and Economics, University of Waikato, Hamilton, 3240, New Zealand; [b]DCU Business School, Dublin City University, Dublin, Ireland

ABSTRACT

This paper investigates, for the first time, the presence of financial contagion among several important Chinese coronavirus concept-based stock indices during the recent COVID-19 global pandemic. We utilize a regime-switching skew-normal (RSSN) methodology to test for contagion through the correlation and coskewness channels while considering structural breaks in the different moments. Our results present evidence of contagion effects, which are robust across identified crisis and non-crisis periods, including that of the Wuhan lockdown. Our empirical results offer investors and policy-makers an additional layer of information when evaluating response mechanisms to major crises through the use of concept-based indices.

KEYWORDS
COVID-19; Chinese stock market; coronavirus; pandemic; contagion; coskewness

JEL CLASSIFICATION
G10; G14; G15

1. Introduction

The beginning of the COVID-19 pandemic in China generated widespread confusion with regard to the true extent of the issues to which the world was confronted. Those living within the city of Wuhan were the first to experience the social, regulatory, and economic repercussions associated with COVID-19, but there existed a substantial period before the initial Chinese phase of the outbreak of the pandemic became an international-scale event. Previous work by Chen et al. (2011) and Wen et al. (2019) identified the existence of substantial information asymmetry between both internationally based and Chinese-based investors. Such differentials were thought to be driven by a delayed response by internationally based investors to the severity of news based on the pandemic that was publicly available. Further informational value can be sourced through several tailored indices that have been created to specifically take account of key corporate performance relating to a variety of dimensions relating to both the deterioration and indeed, the structural success in confronting the challenges within this pandemic. Such concept-based indices include that of Chinese-based coronavirus and influenza index, based on companies that create face masks, an index that measures the performance of disinfectant manufacturers, and, amongst others, an index based on many creators of COVID-19 testing apparatus.

Such research not only adds substantial value when attempting to understand the dynamics within specific elements of the Chinese economy but also, it is important to further our knowledge with regard to broad financial market responses to immense 'black swan' events, such as that of the COVID-19 crisis. Further, we must also understand the dynamics underpinning such a pandemic to be prepared from a political, regulatory, and policy-making standpoint, for the high probability of recurrence and potential for the expansion of crises due to potential future mutation events. Further, the use of bespoke financial series to monitor finer details of crises, such as those selected within our analyses, merits further investigation. While face masks and disinfectant are used to stop the spread of the pandemic, while other novel elements of the series, such as the coronavirus and influenza indices, offer substantial value when attempting to distinguish as to what constitute 'expected' influenza conditions, when compared to novel coronavirus conditions. Investigation of contagion behaviour between such series also provides rich informational value with regard to the expectations and sentiment of

CONTACT Yang (Greg) Hou greg.hou@waikato.ac.nz School of Accounting, Finance and Economics, University of Waikato, New Zealand

investors, and their perceptions as to how such incredibly novel events such as the global pandemic are being counteracted by governing authorities (Sharif, Aloui, and Yarovaya 2020; Bol et al. 2020; Lahmiri and Bekiros 2020).

In this research, we specifically analyse the contagion effects of such indices upon key elements of the Chinese economy using a novel, modified RSSN methodology, focusing specifically on the effects of key dates within the COVID-19 pandemic. We use several COVID-19 concept-based stock price indices as a proxy to measure the impact of COVID-19 in the Chinese stock market as we believe it is best to use a financial index to quantify the financial impact of COVID-19. Our study differs from other research in the literature, as we have used purpose-built financial indices to measure the specific effects of COVID-19. The applied methodology that we adopt in this paper is widely suited for a wide range of applications, and it is particularly suited to study financial market contagion. By selecting financial indices to measure the COVID-19 pandemic impact, we can explore the financial contagion among Chinese stock markets using the traditional financial contagion methods. Results indicate evidence of contagion through correlation and coskewness channels concerning the coronavirus index upon several concept-based indices based on a variety of related, yet theoretically and informatively valuable characteristics relating to the depth and spread of the contracting and retracting waves of the pandemic. Specifically, several interesting findings are presented, where the contagion based on the correlation coefficient is significant in all analysed indices. The use of the correlation coefficient is theoretically supported and validated to serve as primary test for contagion. Further, coskewness contagion is also significant for all the individual analysed pairs, adding further evidence supporting the existence of contagion among COVID-19 concept-based indices. The contagion effects and structural breaks across different channels from all the individual stock indices are found to be significant. Finally, we find evidence of contagion, even under the presence of structural breaks across different moments in mean, variance, and skewness, where our empirical results are also robust across a variety of specifications, particularly to non-crisis and crisis-defined periods when considering the timing of the Wuhan lockdown of January 2020. Our study supports those that have recently investigated the effects of COVID-19 on financial markets, where specifically, the empirical results presented provide investors with new insights into developing investment strategy and diversification opportunities to defend against the severe effects of COVID-19.

The rest of this paper is structured as follows: Section 2 presents a concise overview of previous literature relating to contagion effects, Chinese financial markets, the outbreak of COVID-19 and the selected methodologies. Section 3 presents an overview of the selected data and methodology used in the research presented here, while Section 4 presents an overview and discussion of the results with associated robustness testing procedures. Section 5 concludes.

2. Literature review

Our research draws upon a broad variety of work across a wide range of financial and geographically diverse products, each of which offers substantive information towards our analysis of the Chinese market response to the COVID-19 pandemic. In a piece of research that develops upon novel COVID-based data from the Wind database, Corbet et al. (2021) test for the presence of volatility spillovers from Chinese financial markets during the outbreak of the COVID-19 pandemic upon a broad number of traditional financial assets. They find exceptionally pronounced and persistent impacts of coronavirus on Chinese financial markets compared to that of the traditional and long-standing influenza index. Research focusing on the COVID-19 pandemic has continued to develop at a pace. Funke and Tsang (2020) employed a dynamic-factor modelling approach to derive a composite indicator of China's monetary policy stance in response to the pandemic, presenting an overview of decisions to shore up commercial bank liquidity. Furceri et al. (2021) examined the dynamic impact of recessions on total factor productivity, intensifying deep underlying distortions during recessions. Umar, Kenourgios, and Papathanasiou (2020) analysed the connectedness of global equity indices dependent on ESG performance to find that connectedness exhibits dynamic patterns during three distinct periods: the European sovereign debt crisis, the Greek sovereign debt crisis, and the outbreak of the coronavirus pandemic. Aursland et al. (2020) investigated the ability of a Norwegian-based DSGE methodology to generate state-dependent fiscal multipliers, specifically identifying that both the zero-lower bound on nominal interest rates and DNWR individually can account for higher fiscal multipliers during recessions such as that generated during the recent COVID-19 pandemic. Corbet et al. (2020c) investigated reputational-based contagion during the COVID-19 pandemic, identifying results based on companies that are named, or produce products including the term 'Corona', that indicate behaviour outside of pre-existing interrelationships. Further, Corbet et al. (2020a) identify significant growth in each cryptocurrency returns, and volumes traded, indicating that large cryptocurrencies acted as a store of value in the initial stages of the COVID-19 outbreak in China, while Corbet et al. (2020b) analysed the role of information asymmetry both within and outside of China based on news reports pertaining to be amongst the first to identify the COVID-19 pandemic in Wuhan. The authors identify that the majority of domestically traded Chinese stocks present evidence of significant information flows at a far earlier stage than internationally traded comparative and that cryptocurrencies became informationally synchronized with Chinese equity markets, indicating their use as an investor safe-haven. Such results indicate differential investor behaviour when comparing investors focusing on varying news sources.

With regard to our methodological selection, we develop upon several analyses focusing specifically on contagion, shocks, and structural breaks. Chan, Fry-mckibbin, and Hsiao (2018) utilized a time-varying joint distribution of asset returns, allowing for regime-switching and a joint skew-normal distribution when investigating contagion between US and European financial markets during the subprime and Greek financial crises. The evidence suggests that correlation contagion dominates coskewness contagion. Luo and Zhang (2020) had previously investigated the linear and non-linear dependence structures of risk contagions between global crude oil futures markets and China's agricultural futures markets based on a regime-switching skew-normal (RSSN) model, presenting evidence of correlation and covariance contagions across investigated markets, particularly under turbulent oil market conditions. Similar methodological approaches were also used by Matkovskyy and Jalan (2019) when analysing contagion effects with cryptocurrency markets such as Bitcoin, and traditional financial markets. Batiz-Zuk, Christodoulakis, and Poon (2015) estimated Skew-Normal and Skew-Student t densities for the underlying asset return process and estimate the derived credit loss density using sector default rates based on proprietary data from the Central Bank of Mexico for six firm sectors. The results presented indicated that traditional Basel and vendor-based credit risk models are inadequate due to a lack of consideration of both contagion and non-Gaussian asset returns. Yamaka et al. (2018) found that a Markov Switching model based on skew-normal and skewed student-t distributions as the extension of conventional Markov Switching model outperformed the conventional Markov Switching model when analysing contagion effects among stock markets in Thailand, the United States, and Japan.

3. Data and methodology

3.1. Data

We obtained the data from the WIND database, which is a leading financial data provider in China. The Wind database is widely used by many security companies, fund management companies, insurance companies and banks in China. WIND's customers also include many of the qualified foreign institutional investors (QFII) approved by the China Securities Regulatory Commission. Moreover, the Wind database has been widely used in leading finance research, for example, Carpenter, Lu, and Whitelaw (2020), Allen et al. (2019), Jiang, Lee, and Yue (2010), and Liu and Lu (2007). In this paper, we utilize several concept-based stock price indices that have been recently created by Wind. The Wind concept-based stock price index is a batch of selected indices that meet specific concepts based on the most active emerging markets and related topics. The concept-based stock index is calculated using an equal-weighted weighting method, where the constituent stocks are selected according to the industrial chain linkages and characteristics of the concept theme with consideration of the market turnover and market quotation. The final constituent stock list is selected from all A-share stocks listed and traded on the Shanghai and Shenzhen stock exchanges. Every concept-based index has a base value of 1000 and its base date depends on the specific index. We present the movements of trading volumes for the analysed stock indices in Figure 1. As we can see, the number of shares transacted per day for all indices increase dramatically after the lockdown, and in the period following China's stock market reopening.

We specifically select five COVID-19 concept-based stock price indices denoted as the coronavirus index, the influenza index, the face mask index, the disinfectant index, and the coronavirus testing index from the https://www.wind.com.cn/ database for our empirical analysis.

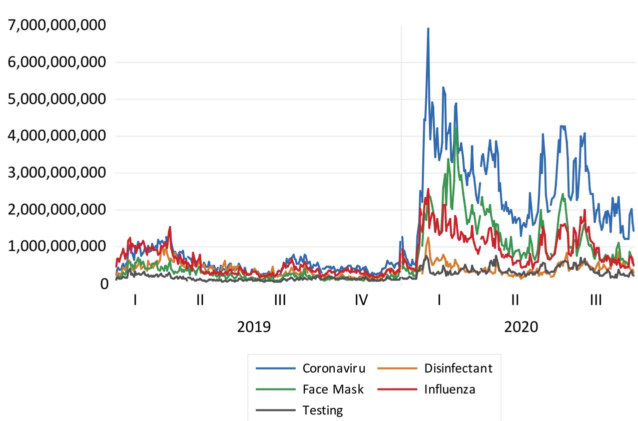

Figure 1. Trading volume of five COVID-19 concept-based stock indices from China's market between 12 February 2019 and 25 September 2020. Note: The above figure plots the trading volume of five COVID-19 concept-based stock indices. The trading volume increases dramatically after February 2020.

Table 1 illustrates key information on the five stock price indices. We select the daily closing price index for the sample period between 12 February 2019 and 25 September 2020. During this sample period, we further divide the period into two sub-samples, the defined non-crisis period (12 February 2019–31 December 2019) and the crisis period (1 January 2020–25 September 2020) as required to establish the parameters of the RSSN methodology. The selection of these periods represents 401 daily observations, with 221 observations utilized in the sample pre-crisis and 180 in the crisis period. The decision to begin the selected sample on 12 February 2019 was based on data availability. Here, we choose 31 December 2019 as a key date relating to the start of the COVID-19 pandemic, as this date is when the WHO officially announced that the world was confronted with a global pandemic that had been sourced and spread from an apparent epicentre in the city of Wuhan.

All five concept-based stock price indices measure the performance of COVID-19 relevant industries pre- and during the global pandemic. The coronavirus index is used as the main proxy to measure the effects of the COVID-19 virus on financial markets. The coronavirus index is created using an equal weight approach including 115 publicly listed Chinese companies that are heavily involved in producing diagnostic reagents, vaccines, antibiotics, antivirals, and masks related to pneumonia. The influenza virus is widely known as an acute respiratory infection, which is highly contagious and spreads quickly. The Wind database creates a special concept-based stock price

Table 1. Some key comparisons of the five COVID-19 concept-based stock index.

Indices	Coronavirus	Face Mask	COVID-19 Testing	Disinfectant	Influenza
Release Date	22 January 2020	4 February 2020	20 April 2020	7 February 2020	10 February 2020
Base Date	31 December 2011	4 February 2019	31 December 2017	7 February 2019	1 January 2015
Base Point	1,000	1,000	1,000	1,000	1,000
Weighting Methods	Equally Weighted	Equally Weighted	Equally Weighted	Equally Weighted	Equally Weighted
No. of Components	115	39	24	21	35

Note: We specifically select five important concept-based stock price indices, denoted as the coronavirus index, the influenza index and the face mask index, the disinfectant index and the coronavirus testing index from the Wind database for our empirical analysis. We select the daily closing price index for the sample period between 12 February 2019 and 25 September 2020. During this sample period, we further divide into two sub-samples as non-crisis period (12 February 2019–31 December 2019) and crisis-period (1 January 2020–25 September 2020) as required by the RSSN model.

index, the influenza index, which comprises 35 listed A-share companies that are involved in producing cold medicines, vaccines, R&D, and manufacturing, to track the performance of the related companies. Disinfectants are mainly used to eliminate the transmission route of infectious diseases, thereby controlling the spread of infectious diseases. The disinfectant index includes 21 companies that manufacture disinfectants, peracetic acid and bleach powder. The Coronavirus testing index includes 24 related companies that develop and manufacture coronavirus testing products. We also use the face mask index (also known as Antiseptic Gauze index) that includes 39 listed Chinese companies in the field of producing face masks and raw materials from SSE and SZSE. The face mask index simply provides a measure of the performance of the face masks producing industry after the outbreak of the COVID-19. All five stock price indices demonstrate the impact of the unexpected outbreak of COVID-19 on the stock market in China.

Figure 2 plots the return series of all stock index returns. We can see that all five stock index returns experience higher fluctuations after the WHO announced the first unknown case of COVID-19, which are of particular interest. Table 2 presents the descriptive statistics for the return series of all five COVID-19 concept-based stock indices over a non-crisis period (12 February 2019 through 31 December 2019) and the crisis period (1 January 2020 through 25 September 2020). These summary statistics motivate the use of the RSSN model to capture the characteristics of financial market data. We can see that there are substantial changes in these statistics during the two periods. The mean index returns in the non-crisis period are generally lower than those in the crisis period except the disinfectant index. The standard deviations of returns suggest greater fluctuation in all stock index returns especially during the COVID-19 pandemic. Table 2 also presents evidence of the non-normality of all the stock index returns in both periods.[1]

3.2. Methodology

This section describes the testing procedure we use and develop to investigate contagion and structural breaks, specifically based on the tests of Chan, Fry-mckibbin, and Hsiao (2018). This allows us to consider both linear and non-linear dependence structures of the COVID-19 concept-based stock price indices for financial contagion. For the RSSN model, the asset returns y_t are assumed to follow a multivariate skew-normal distribution under each regime. This assumption allows us not only to capture some well-known characteristics of financial data, for example, asymmetry, heavy tails, heteroskedasticity, linear and non-linear comovement of asset returns, but also controls parameters to be varied in different states. Considering a multivariate skew-normal distribution for a set of asset returns y_t then the model can be specified as:

$$y_t = \mu_{s_t} + \Omega_{s_t} Z_t + \varepsilon_t, \tag{1}$$

$$\varepsilon_t \sim^{iid} N(0, \Sigma_{s_t}), \tag{2}$$

$$Z_t \overset{iid}{\sim} N(c1_m, I_m) 1(Z_{jt} > c, j = 1, \ldots, m). \tag{3}$$

The regime s_t is assumed to have two states, $s_t \in 0, 1$. Two sets of regime-dependent parameters $(\mu_0, \Omega_0, \Sigma_0)$ and $(\mu_1, \Omega_1, \Sigma_1)$ are available for two different regimes. The means μ_{s_t}, coskewness Ω_{s_t}, and the error cross-covariances Σ_{st} from Equations 1 to 3 are allowed to change in regime s_t=0 to regime s_t=1. Contagion is measured as changes in the parameters controlling market linkages of correlation and coskewness during the second period. Structural breaks are measured

[1]We also carry out an additional test of Doornik and Hansen (2008)'s omnibus test for multivariate normality and the test results reject the multivariate normality hypothesis on the five return series in both non-crisis and crisis periods at the one percent level. We also apply the Mardia (1970) skewness and kurtosis test for assessing multivariate skewness and kurtosis measures under normality condition and the results again reject the null that skewness and kurtosis measures point to a multivariate normal distribution for the five return series in both non-crisis and crisis periods at the one percent level

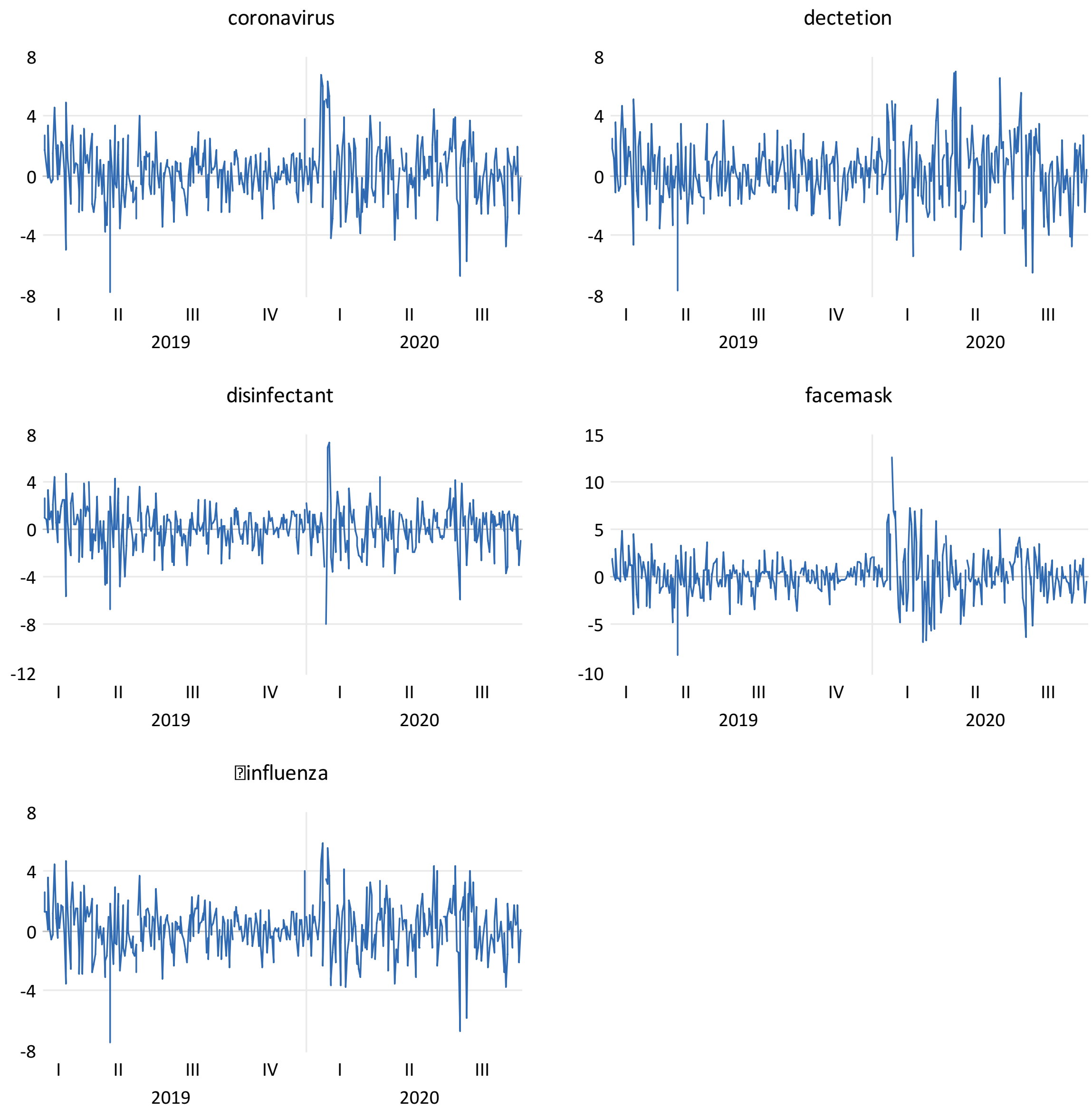

Figure 2. Return series of five COVID-19 concept-based stock indices from China's market between 12 February 2019 and 25 September 2020. Note: The above Figure plots the return series of all stock index returns. We can see that all five stock index returns experience higher fluctuations after the WHO announced the first unknown case of COVID-19, which are of particular interests.

as changes in the moment parameters of the mean, variance, and skewness in the second regime. Equations 1 to 3 can be rewritten as:

$$y_t = X_t\beta_{s_t} + \varepsilon_t, \tag{4}$$

$$\varepsilon_t \sim^{iid} N(0, \Sigma_{s_t}), \tag{5}$$

where $X_t = (I_m, I_m \otimes Z_t'), \beta_{s_t} = (\mu_{st}', \omega_{st}')', \omega_{s_t} = vec(\Omega_{st}')$. The state of the regime s_t is specified as:

$$Pr(s_t = 1|s_{t-1} = i) = p_{it}, i \in 0, 1, \tag{6}$$

where p_{it} are fixed constants. The parameters of the RSSN model can then be specified:

$$\Theta = (\beta_0, \beta_1, \Sigma_0, \Sigma_1). \tag{7}$$

We next substitute a Bayesian estimation approach for the typical likelihood function approach:

$$f(y|Z, \Theta, s) = (2\pi)^{-\frac{mT}{2}} \prod_{t=1}^{T} |\Sigma_{s_t}|^{-\frac{1}{2}} \exp\left\{ \begin{array}{l} -\frac{1}{2}\sum_{t=1}^{T}\left[y_t - X_t\beta_{s_t}\right]' \\ \Sigma_{s_t}^{-1}\left[y_t - X_t\beta_{s_t}\right] \end{array} \right\}, \tag{8}$$

Table 2. Descriptive statistics of the return.

	Coronavirus	Face Mask	Testing	Disinfectant	Influenza
Non-crisis period (12 February 2019–31 December 2019)					
Mean	0.1475	0.0493	0.1478	0.1294	0.1108
Median	0.2945	0.1206	0.1252	0.1893	0.2184
Max	4.8551	4.7593	5.1035	4.5863	4.7099
Min	−7.8218	−8.1334	−7.7239	−6.6714	−7.4964
Std. Dev.	1.6725	1.6314	1.6634	1.7357	1.5354
Skewness	−0.5292	−0.6993	−0.3535	−0.5024	−0.4302
Kurtosis	5.1382	5.9499	4.9729	4.4504	5.4461
P-value: JB test	0.0000	0.0000	0.0000	0.0000	0.0000
	Coronavirus	Face Mask	Testing	Disinfectant	Influenza
Crisis period (1 January 2020–25 September 2020)					
Mean	0.2979	0.3282	0.3575	0.0714	0.2130
Median	0.3609	0.0253	0.6263	0.2152	0.3004
Max	6.6853	12.5368	6.9976	7.2188	5.8757
Min	−6.7179	−6.8429	−6.4797	−7.9819	−6.7425
Std. Dev.	2.1770	2.8155	2.4564	1.9186	1.9920
Skewness	0.0415	0.5365	−0.0918	−0.1722	−0.1075
Kurtosis	3.7826	4.9392	3.1641	5.6973	3.7657
P-value: JB test	0.0000	0.0000	0.0000	0.0000	0.0000

Note: *JB*: the p-value of Jarque-Bera test statistic for normality.

where $\Theta = (\beta_0, \beta_1, \sigma_0, \sigma_1)$ and $s_t \in 0, 1$. The priors for the parameters are:

$$\beta_{s_t} \sim N(\underline{\beta}, \underline{V}_\beta), \tag{9}$$

$$\Sigma_{s_t} \sim IW(\underline{\tau}_\Sigma, \underline{S}_\Sigma), \tag{10}$$

$$\Pr(s_t = 1 | s_{t-1} = i) = p_{it}, \tag{11}$$

$$\Pr(s_t = 0 | s_{t-1} = i) = 1 - p_{it}, \tag{12}$$

where $IW(\underline{\tau}_\Sigma, \underline{S}_\Sigma)$ denotes the inverse-Wishart distribution with degree of freedom $\underline{\tau}_\Sigma$ and scale matrix $\underline{S}_\Sigma$. The above model parameters are estimated by using a Bayesian approach. The Markov Chain Monte Carlo methods are applied to obtain draws from the posterior distribution for the analysis, please refer Chan, Fry-mckibbin, and Hsiao (2018) for further technical details.

Table 4. Model selection based on the log of the Bayes factor.

Value of $Ln(BF_{ru})$	Evidence categories
$(0, \infty)$	Evidence in support of Model M_r
(−1.15, 0)	Very slight evidence in support of Model M_u
(−2.30, −1.15)	Slight evidence in support of Model M_u
(−4.60, −2.30)	Strong evidence in support of Model M_u
$(-\infty, -4.60)$	Decisive evidence in support of Model M_u

The choice of Bayes factor threshold is based on the scale of evidence. The log of the Bayes factor $Ln(BF_{ru}) = ln(p(y|M_r)) - ln(p(y|M_u))$. This table is taken from Chan, Fry-mckibbin, and Hsiao (2018).

Chan, Fry-mckibbin, and Hsiao (2018) discuss the testing procedures for contagion and structural breaks. The restrictions on the parameters and the method used to examine each hypothesis are provided in Table 3, and the choice of the log of the Bayes factor threshold value for model selection is shown in Table 4.

Next, we attempt to measure specific contagion effects. Correlation tests contagion between the selected markets based on an increase in the correlation coefficients as in Forbes and Rigobon (2002). The contagion change test between asset markets i and j is $\rho_{ij,1} - \rho_{ij,0} > 0$. The probability of correlation contagion between the selected markets is therefore:

$$Pr(\rho_{ij,1} - \rho_{ij,0} > 0 | y, M_u), \tag{13}$$

The test for joint correlation contagion between m-1 pairs of asset returns with market j is $\Upsilon_0 \leq \Upsilon_1$, where Υ_1 is the sum of the individual

Table 3. Summary of the restrictions on the model parameters and the hypothesis evaluation methods for the tests for contagion and structural breaks.

Tests	Method	Market i	i
Contagion tests ($i \neq j$)			
Correlation	p	$\rho_{ij,0} < \rho_{ij,1}$	$\gamma_0 < \gamma_1$
Coskewness	BF	$\omega_{ij,0} = \omega_{ji,0}$	$\Omega_0 = \Omega_1$
Correlation & Coskewness	BF	$\rho_{ij,0} = \rho_{ij,1}, \omega_{ij,0} = \omega_{ji,0}$	$\gamma_0 = \gamma_1, \Omega_0 = \Omega_1$
Structural break tests (i)			
Mean	p	$\mu_{i,0} > \mu_{i,1}$	$\mu_0 > \mu_1$
Variance	p	$\sum_{ii,0} < \sum_{ii,1}$	$\sum_0 < \sum_1$
Skewness	BF	$\omega_{ii,0} = \omega_{ii,1}$	$\omega_0 = \omega_1$
Mean, Variance, & Skewness	BF	$\mu_{i,0} = \mu_{i,1}, \sum_{ii,0} = \sum_{ii,1}, \omega_{ii,0} = \omega_{ii,1}$	$\mu_0 = \mu_1, \sum_0 = \sum_1, \omega_0 = \omega_1$
Joint contagion ($i \neq j$) and structural break tests (i)			
All	BF	$\mu_{i,0} = \mu_{i,1}, \sum_{ii,0} = \sum_{ii,1}, \omega_{ii,0} = \omega_{ii,1}$ & $\rho_{ij,0} = \rho_{ij,1}, \omega_{ij,0} = \omega_{ji,0}$	$\mu_0 = \mu_1, \sum_0 = \sum_1, \omega_0 = \omega_1$ $\gamma_0 = \gamma_1, \Omega_0 = \Omega_1$

Note: The tests are for a change in each parameter in the crisis period $s_t = 1$ compared to a non-crisis period $s_t = 0$. The method of hypothesis evaluation for each test is indicated in the table. p denotes that a decision is probability based. BF denotes that a decision is based on the log of the Bayes factor threshold. This table is taken from Chan, Fry-mckibbin, and Hsiao (2018).

correlation coefficients and $\Upsilon_1 = \sum_{i=1}^{m}\sum_{j\neq i}^{m}\rho_{ij,l}$. The coskewness contagion test is based on the asymmetric dependence of returns i and j in regime $s_t = 0$ compared with $s_t = 1$,

$$\omega_{ij,s_t=0} \neq \omega_{ji,s_t=1}, i \neq j. \tag{14}$$

where $\omega_{ij,s_t=1}$ is the coskewness coefficient in the regime $s_t = 1$ and $\omega_{ij,s_t=0}$ is the coskewness coefficient in the regime $s_t = 0$.

3.3. Identifying structural breaks

We next develop the hypotheses on which to test for structural breaks in the mean returns for asset market i during $s_t = 1$ compared to $s_t = 0$ is based on a reduction in the mean. The probability for market i is defined as:

$$Pr(\mu_{i,1} - \mu_{i,0} < 0|y, M_u), \tag{15}$$

The relevant probability of the joint test is:

$$Pr(\sum_{i=1}^{m}\mu_{i,1} - \mu_{i,0} < 0|y, M_u), \tag{16}$$

The second type of test for structural breaks considers the change in the variance of the returns if market i is in the crisis period compared to the non-crisis period,

$$Pr(\sum_{ii,1} - \sum_{ii,0} > 0|y, M_u), \tag{17}$$

The joint test for a structural break in the variance for all m asset markets is based on the restriction $\sum_{i=1}^{m}(\sum_{ii,1} > \sum_{ii,0})$. Further, the structural break tests in skewness captures a change in tail behaviour of the returns i in regime $s_t = 1$ compared to regime $s_t = 0$ and is given by:

$$\omega_{ii,s_t=0} \neq \omega_{ii,s_t=1}. \tag{18}$$

The hypothesis that $\omega_{ii,s_t=0} = \omega_{ii,s_t=1}$ can be used for testing for evidence of a structural break in the skewness for market i across regimes $s_t = 0$ and $s_t = 1$. The hypothesis can be tested by comparing the unrestricted model M_u with the restricted model M_r. We let all regime-specific parameters vary freely across the two regimes in M_u while there is no shift in the return skewness for the asset market i between the two regimes in M_r. This restriction suggests that return skewness in the two periods remains the same under the restricted model M_r. The Bayes factor comparing the restricted model M_r and unrestricted model M_u for the skewness change break is computed using the Savage-Dicky density ratio:

$$BF_{ru} = \frac{\pi(\omega_{ii,1} - \omega_{ii,0} = 0|y, M_u)}{\pi(\omega_{ii,1} - \omega_{ii,0} = 0|M_u)}, \tag{19}$$

where $\pi(\omega_{ii,1} - \omega_{ii,0} = 0|y, M_u)$ and $\pi(\omega_{ii,1} - \omega_{ii,0} = 0|M_u)$ are the posterior and prior densities of $\omega_{ii,1} - \omega_{ii,0}$ evaluated at point 0. The priors $\omega_{ii,1}$ and $\omega_{ii,0}$ follow a normal distribution. The restricted model for the joint version of the test for the skewness break in all m markets is $\omega_{ii,0} = \omega_{ii,1}$.

3.3.1. Joint contagion and structural break test

An appealing feature of the RSSN model is that it allows the testing of the joint contagion and structural breaks across all the considered financial markets. The unrestricted RSSN model has the sets of regime-specific parameters of μ_0 and μ_1, $\sum_0$ and $\sum_1$, and ω_0 and ω_1 while the restricted model M_r depends on the constraints on these parameters. The Bayes factor for comparing model M_r with the unrestricted model M_u is:

$$BF_{ru} = \frac{\pi(\mu_{i,1} - \mu_{i,0} = 0, \sum_{ii,1} - \sum_{ii,0}, \omega_{ii,1} - \omega_{ii,0} = 0|y, M_u)}{\pi(\mu_{i,1} - \mu_{i,0} = 0, \sum_{ii,1} - \sum_{ii,0}, \omega_{ii,1} - \omega_{ii,0} = 0|M_u)} \tag{20}$$

where $\pi(\mu_{i,1} - \mu_{i,0} = 0, \sum_{ii,1} - \sum_{ii,0}, \omega_{ii,1} - \omega_{ii,0} = 0|y, M_u)$ and $\pi(\mu_{i,1} - \mu_{i,0} = 0, \sum_{ii,1} - \sum_{ii,0}, \omega_{ii,1} - \omega_{ii,0} = 0|M_u)$ are the posterior and prior densities for $\mu_{i,1} - \mu_{i,0} = 0, \sum_{ii,1} - \sum_{ii,0}$ and $\omega_{ii,1} - \omega_{ii,0}$ evaluated at point 0.

4. Results

For the MCMC estimation, we run a total of 100,000 iterations after discarding 15,000 draws as the burn-in. To reduce estimation bias, every 10 draws of the 85,000 iterations are recorded and the final total of 8,500 draws are used for the computations of posterior results. Next, we need to determine the specification structure with regard to the timing of the identified regime change. The initial value for the probability of

Table 5. Empirical results of the contagion and structural break tests for the selected COVID-19 related financial indices.

Tests	Method	Coronavirus	Face Mask	Testing	Disinfectant	Influenza	i
Contagion tests ($i \neq j$)							
Correlation	p		0.97	0.98	0.99	0.99	1.00
Coskewness	*BF*		−12.85	−10.86	−4.40	−9.20	−283.07
Correlation & Coskewness	*BF*		−15.21	−12.74	−7.14	−11.84	−282.64
Structural break tests (i)							
Mean	p	1.00	0.61	1.00	0.77	1.00	0.96
Variance	p	1.00	1.00	1.00	1.00	1.00	1.00
Skewness	*BF*	−15.58	−22.34	−0.48	0.48	−5.25	−77.13
Mean & Variance & Skewness	*BF*	−24.36	−62.38	−7.50	−4.80	−11.02	−13.69
Joint contagion ($i \neq j$) and structural break tests (i)							
All	*BF*		−36.21	−42.31	−14.36	−15.88	−296.32

Note: Contagion is measured with respect to the coronavirus index. p denotes that a decision is probability based. *BF* denotes that a decision is based on the log of the Bayes factor threshold. Non-crisis period: 12 February 2019–31 December 2019. Crisis-period: 01 January 2020–25 September 2020.

being in regime 0 is set to $\Pr(s_t=0) = 0.99$ for the period 12 February 2019 through 12 December 2019. As discussed, the WHO was initially informed of cases of pneumonia of unknown aetiology, as detected in Wuhan in late 2019. However, on 31 December 2019, the WHO announced that they had identified what was to be considered a global pandemic. The probability of being in regime 0 decreases from 0.99 on 3 December 2019 to 0.01 on 5 February 2020. The probability of being in regime 1 is equal to $\Pr(s_t=1) = 0.99$ during the period 2 February 2020 through 25 September 2020.[2]

This section presents the empirical results using the RSSN model for contagion and structural breaks in Table 5. The RSSN model is applied to each stock index individually and then as a combination of all stock indices jointly, to investigate whether there is evidence of contagion in the correlation and/or coskewness, with further testing for evidence of structural breaks in mean, variance and/or skewness processes. As can be observed from Table 5, the top panel considers evidence of contagion between the coronavirus index and several other concept-based stock indices via correlations and coskewness; the middle panel examines evidence of structural breaks in the mean, variance and coskewness of each stock index return; and the lower panel implements a joint test of contagion and structural breaks.

Contagion is calculated concerning the coronavirus index as the source of shocks for the other four concept-based stock indices. The correlations in our contagion tests and mean and variance in structural breaks are probability-based. Coskewness, correlation, and coskewness in contagion tests and skewness, mean, variance, and skewness in structural break tests are based on the log of the Bayes factors.

4.1. Contagion effects

We first discuss the empirical results for contagion without considering the potential structural break effects. The upper panel of Table 5 shows an increase in the correlation coefficient between the coronavirus index return and other key concept-based stock indices returns as reflected by the probability of contagion. In particular, the probability of contagion between the coronavirus returns and face mask, testing, disinfectant, and influenza returns are 0.97, 0.98, 0.99 and 0.99, respectively. We also observe that the probability of joint contagion through the correlation channel is equal to one. Overall, we find evidence of contagion through the correlation channel in all the individual and combined markets. There is also decisive evidence presented supporting coskewness changes for the face mask, testing and influenza index returns, and strong evidence to support coskewness contagion for the coronavirus-disinfectant pair. The joint test for a coskewness change for a combined five COVID-19 related indices also shows decisive evidence of contagion with a log of the Bayes factor of −283.07.

When the correlation and coskewness changes are tested separately, the results present evidence to support the contagion effects for each pair. We then investigate the joint test, specifically analysing whether contagion occurs jointly through the

[2] We have tried different specifications of the prior estimations and our results remain quantitatively unchanged.

correlation and coskewness channels between the coronavirus index and individual stock index return, and the combination of all COVID-19 related stock index returns. The joint test confirms that contagion occurs jointly through both the correlation and coskewness effects with decisive evidence for each COVID-19 related indices and a combination of all the indices. In particular, the contagion effects to the face mask index play a more important role in the correlation and coskewness channels with the lowest logarithmic Bayes factor of −15.21 among all the individual indices. This result demonstrates a closer connection between coronavirus-related stocks and face mask manufacturing-related stocks. The contagion effect for coronavirus-testing pair is also very strong based on a second-lowest logarithmic Bayes factor of −12.74, highlighting the perceived importance in developing and manufacturing testing products to fight for COVID-19 as identified by financial market investors. There is decisive evidence to support contagion effect for coronavirus-disinfectant pair, supporting the need of those companies that manufacture face mask and related materials to protect against COVID-19. Finally, there is decisive evidence of contagion between the coronavirus and influenza indices as the manufacture of influenza medicines and vaccines are also seen as helping to prevent the spread of infectious diseases. These contagion effects suggest the strong connections among the COVID-19 related stock price indices based on different industries and highlight different pathways for fighting the COVID-19 virus from producing face masks to disinfectants, to testing products and even influenza medicines manufacturing industries.

4.2. Structural breaks

Next, we explore the structural break tests for all the COVID-19 related stock index returns in the different moments. The probability of a structural break in the mean is 1.00, 0.61, 1.00, 0.77 and 1.00 for each of the coronavirus index, face mask index, testing index, disinfectant index, and influenza index, respectively. There is also evidence of a structural break in the variance parameters for all five COVID-19 related stock indices with a probability of 1.00. Also, we find decisive evidence of a structural break in the skewness parameter for the coronavirus, face mask and influenza indices based on Bayes factors.

There is evidence of a structural break of all the moments mean, variance and skewness for the coronavirus index and the influenza index. We notice that the probability of a structural break in the mean parameter for the face mask index is only 0.61; however, the face mask index is affectedly by structural breaks in the second and third moments. The COVID-19 testing index is affected by structural breaks in the first and second moments but not in the third moment. The probability of a change in the mean is 0.77 for the disinfectant index. Moreover, there is no evidence of a break in the third moment for the disinfectant index based on the value of the logarithmic Bayes factor while there is decisive evidence of a regime change in the second moment for the disinfectant index. These examples illustrate the necessity of examining the potential breaks at different moments as the results could change dramatically.

Considering all five stock indices jointly, we find ample evidence of a structural break in the means with a probability of 0.96 during the COVID-19 crisis. Moreover, the higher-order moments for the joint markets are also found to be affected by structural breaks. For example, the probability of a joint structural break invariance is 1, and there is decisive evidence of a joint structural break in skewness moment with a Bayes factor in the logarithm of −77.13. When considering the mean, variance, and skewness jointly for structural breaks, this all-moment test clearly shows decisive evidence of a structural break with a Bayes factor in logarithms of −13.69. To summarize, the results clearly show that the variance channel on structural breaks dominates the mean channel and skewness channel.

4.3. Joint tests of contagion and structural breaks

The lower panel of Table 5 shows the results for the presence of contagion and structural breaks simultaneously for each COVID-19 related stock index as well as for a combination of all the stock indices together. We found decisive evidence of joint contagion and structural breaks in all individual stock indices. In particular, the contagion effect between the coronavirus index and face mask index is the second-largest based on a Bayes factor of −36.21. The contagion effect for the coronavirus-testing pair is the largest with a Bayes factor of −42.31. The coronavirus-disinfectant and the coronavirus-influenza pairs are ranked as the third and fourth based on the strength of Bayes factors. These contagion effects are confirmed from different categorical companies that manufacture face mask and related materials, develop, and manufacture the specific COVID-19 diagnostic testing products, manufacture the disinfectant products, and develop and produce influenza medications and vaccines. These results strongly suggest that the RSSN model provides evidence of contagion changes for several key COVID-19 related stock indices during the global pandemic by considering the structural breaks. The joint test for the combined markets also presents decisive evidence of contagion and structural breaks, where the joint test produces a value of the log Bayes factor as −296.32, highlighting the importance of investigating potential contagion and structural breaks jointly.

4.4. Robustness checks

We also undertake sensitivity analysis to check the robustness of our results. As in the previous example, we choose 31 December 2019 as a key date to decide the non-crisis and crisis period, which is required for the RSSN model. In the following robustness checks, we use alternative crisis and non-crisis dates to check if results would still hold. We choose 23 January 2020, when the central government of China imposed a lockdown in Wuhan and other cities in Hubei province to quarantine the centre of an outbreak of COVID-19, as a key date to determine the non-crisis and crisis period. This action is widely known as the Wuhan lockdown. We, therefore, explore the effects of different non-crisis/crisis dates on testing for

Table 6. Empirical results of the contagion and structural break tests for the selected COVID-19 related financial indices.

Tests	Method	Coronavirus	Face Mask	Testing	Disinfectant	Influenza	i
Contagion tests ($i \neq j$)							
Correlation	*p*		0.91	0.93	0.97	0.95	1.00
Coskewness	*BF*		−8.97	−8.84	−5.22	−7.35	−270.66
Correlation & Coskewness	*BF*		−10.07	−10.03	−6.86	−8.80	−267.63
Structural break tests (i)							
Mean	*p*	1.00	0.75	0.99	0.70	1.00	0.97
Variance	*p*	0.99	1.00	1.00	0.98	1.00	1.00
Skewness	*BF*	−11.80	−20.72	−3.18	0.67	−7.38	−82.11
Mean & Variance & Skewness	*BF*	−14.47	−52.22	−8.88	−3.89	−11.70	−10.71
Joint contagion ($i \neq j$)							
and structural break tests (i)							
All	*BF*		−26.12	−36.11	−15.18	−11.94	−278.34

Note: Contagion is measured with respect to the coronavirus index. *p* denotes that a decision is probability based. *BF* denotes that a decision is based on the log of the Bayes factor threshold. Non-crisis period: 12 February 2019–23 January 2020. Crisis-period: 3 February 2020–25 September 2020.

Table 7. Additional robustness check: Empirical results of the contagion and structural break tests for the selected COVID-19 related financial indices.

Tests	Method	Coronavirus	Face Mask	Testing	Disinfectant	Influenza	i
Contagion tests ($i \neq j$)							
Correlation	*p*		0.86	0.90	0.95	0.93	1.00
Coskewness	*BF*		−11.06	−8.50	−4.72	−7.64	−345.08
Correlation & Coskewness	*BF*		−11.85	−9.58	−5.97	−8.84	−341.84
Structural break tests (i)							
Mean	*p*	1.00	0.74	0.99	0.71	1.00	0.97
Variance	*p*	0.98	1.00	1.00	0.97	1.00	1.00
Skewness	*BF*	−15.41	−14.85	−3.50	0.80	−7.52	−77.67
Mean & Variance & Skewness	*BF*	−19.16	−29.14	−8.91	−3.39	−10.89	−5.51
Joint contagion ($i \neq j$)							
and structural break tests (i)							
All	*BF*		−31.08	−29.22	−14.26	−11.45	−347.35

Note: Contagion is measured with respect to the coronavirus index. *p* denotes that a decision is probability based. *BF* denotes that a decision is based on the log of the Bayes factor threshold. Non-crisis period: 12 February 2019–11 March 2020. Crisis-period: 12 March 2020–25 September 2020.

contagion and structural breaks using the recently proposed SSRN model, where the empirical results are reported in Table 6.

The upper panel of Table 6 clearly shows evidence of correlation contagion between the coronavirus index and face mask index, COVID-19 testing index, disinfectant index, and influenza index as the probabilities of contagion range from 0.91 to 0.97. On the coskewness side, the contagion test provides decisive evidence in all COVID-19 related stock indices based on the Bayes factor ranging from −5.22 to −8.97. The coronavirus-face mask pair contributes to a greater proportion of contagion change in the coskewness channel as this pair has the smallest Bayes factor of −8.97 among other pairs. Moreover, the coronavirus-testing index pair contributes to the second-largest contagion effects with a log Bayes factor of −8.84. The joint test for correlation and coskewness changes also presents evidence of contagion with the logs of the Bayes factor being −10.07, −10.03, −6.86 and −8.80 for the face mask index, testing index, disinfectant index, and influenza index pairs, respectively. The face mask-related stocks are more closely connected to those stocks included in the coronavirus index. The 24 companies that make up the COVID-19 testing index have a closer connection with the coronavirus. In general, there is evidence to support contagion from correlation, coskewness or joint correlation and coskewness channels. The coskewness channel of contagion dominates the correlation channel as the coskewness change provides decisive support for each index.

The above results demonstrate the contagion effects of four important and closely related stocks through different channels. Also, we find decisive evidence of joint contagion through correlation and/or coskewness channels for all the combined market with a Bayes factor of −267.63. The results for structural break tests are reported in the middle panel of Table 6. The probabilities of structural breaks occurring in the mean are 1.00, 0.99 and 1.00 for the coronavirus index, COVID-19 testing index and influenza index. The probabilities of a structural break in the mean are 0.75 and 0.70 for the face mask index and disinfectant index. As observed, the probabilities of structural breaks occurring in the variance range from 0.98 to 1.00 for all five COVID-19 stock indices. Structural break tests indicate that the coronavirus and influenza indices are individually affected by breaks in mean, variance, and skewness. The face mask index is affected by break in variance and skewness. There is decisive evidence of a break in mean and variance for the COVID-19 testing index while strong evidence of a break in skewness. However, the disinfectant index is only affected by breaks in the variance. The test results of joint structural breaks in the mean, variance and skewness confirm evidence of breaks for all the individual stock price index except the disinfectant index. A Bayes factor of −3.89 for the disinfectant index suggests strong evidence of joint breaks in the mean, variance, and skewness. For the combined stock indices, we find evidence of a joint breakthrough mean, variance, and skewness.

The lower panel of Table 6 presents results based on the presence of contagion and structural breaks simultaneously. The RSSN model finds evidence of contagion and structural breaks in all individual stock price index. The evidence of joint contagion and structural breaks is important based Table 7 on the value of the log Bayes factor for every individual index. As the joint test for the combined market serves as an overall test for a crisis and contagion, the evidence is overwhelming and decisive with a value of log Bayes factor at −278.34. Most importantly, comparing results based on the different crisis- and non-crisis dates, we find that most results remain unchanged.[3]

5. Conclusion

In this research, contagion is analysed through the channels of correlation and coskewness in the non-crisis period (before the WHO announces the outbreak of pneumonia of unknown cases on 31 December 2019) in comparison to the crisis period identified as the period thereafter. In particular, we test for the existence of contagion effects

[3]The WHO declared COVID-19 as a global pandemic on 11 March 2020. We also carry out additional robustness check using alternative dates for the non-crisis period (12 February 2019–11 March 2020) and crisis period (12 March 2020–25 September 2020). Our results remain unchanged.

using several recently constructed COVID-19 concept-based indices derived from China's stock market. We also consider potential structural breaks in a range of different moments.

Several interesting findings are presented. Firstly, financial market contagion, based specifically upon the correlation coefficient, is found to be significant in all the individual stock indices considered including the face mask index, COVID-19 testing, disinfectant, and influenza, indices. Second, the evidence of coskewness contagion is also decisive for all the individual pairs tested, adding further evidence to support contagion among COVID-19 concept-based indices. Thirdly, the moment break tests present evidence supporting the existence of a flight to safety. During the global pandemic, the coronavirus index and influenza index are only financial indices presenting breaks within all three moments (mean, variance and skewness). The presence of structural breaks in the mean, variance and skewness indicates that more risk averse investors appear to be leaving the market en mass, hence the existence of comovements of the asset returns. In practice, investors are more risk appetite for the stocks that included in the coronavirus and influenza indices after the outbreak of COVID-19 pandemic, compared to other financial indices. The flight to safety phenomenon can be understood when the coronavirus index is the source of crisis period (the COVID-19 pandemic). Finally, the joint test for contagion and structural breaks are also evidenced in, highlighting the need to consider contagion, and breaks in a multivariate setting as it is often to conduct contagion analysis on a bivariate basis. Further, we must note that our empirical results are also robust to different specifications of crisis/non-crisis dates in general.

Our findings have important policy implications. In particular, through the use of such concept-stocks, we show that a significant breadth and depth of informative value can be added, not only through the presentation of the levels of such indices but also through the interactions between them. Specifically, such information can aid portfolio diversification practices, as investors attempt to hedge against such re-occurrences in the future. Such concept-stocks also provide valuable insights to central banks and governments when attempting to generate counter-responses in terms of monetary policy decision-making and clear, informationally driven government health guidance. While the world attempted to make sense of the chaos central to the escalation of the COVID-19 pandemic, such concept-based indices, and their inherent dynamics, allow detailed evaluations as to the specific stages that governments find themselves in, as measured by investor-based perceptions within efficient and liquid financial markets. Further, identification and the continued monitoring of interactions between traditional influenza indices and coronavirus indices present valuable insights into the public perceptions surrounding the fight against this global pandemic. An interesting direction for future research would surround the time-varying geographical performance of similar concept-based indices, with estimation linked with the worldwide spread of the COVID-19 pandemic. Such analysis would present strong evidence as to the level of surprise that manifested within financial markets, particularly as investors sought safe haven strategies during this incredible 'black-swan' event.

Disclosure statement

No potential conflict of interest was reported by the author(s).

ORCID

Shaen Corbet http://orcid.org/0000-0001-7430-7417
Yang (Greg) Hou http://orcid.org/0000-0003-0017-9912

References

Allen, F., Y. Qian, G. Tu, and F. Yu. 2019. "Entrusted Loans: A Close Look at China's Shadow Banking System." *Journal of Financial Economics* 133 (1): 18–41. doi:10.1016/j.jfineco.2019.01.006.

Aursland, T., I. Frankovic, B. Kanik, and M. Saxegaard. 2020. "State-dependent Fiscal Multipliers in Nora - a Dsge Model for Fiscal Policy Analysis in Norway." *Economic Modelling* 93: 321–353. doi:10.1016/j.econmod.2020.07.017.

Batiz-Zuk, E., G. Christodoulakis, and S.-H. Poon. 2015. "Credit Contagion in the Presence of Non-normal Shocks." *International Review of Financial Analysis* 37: 129–139. doi:10.1016/j.irfa.2014.11.014.

Bol, D., M. Giani, A. Blais, and P. Loewen. 2020. "The Effect of Covid-19 Lockdowns on Political Support: Some Good News for Democracy?" *European Journal of Political Research*. 60(2): 497-505.

Carpenter, J. N., F. Lu, and R. F. Whitelaw. 2020. "The Real Value of China's Stock Market." *Journal of Financial Economics*139 (3):679-696.

Chan, J. C., R. A. Fry-mckibbin, and C. Y.-L. Hsiao. 2018. "A Regime Switching Skew-normal Model of Contagion." *Studies in Nonlinear Dynamics & Econometrics* 23: 1.

Chen, S., Z. Sun, S. Tang, and D. Wu. 2011. "Government Intervention and Investment Efficiency: Evidence from China." *Journal of Corporate Finance* 17 (2): 259–271. doi:10.1016/j.jcorpfin.2010.08.004.

Corbet, S., G. Hou, Y. Hu, C. J. Larkin, and L. Oxley. 2020a. "Any Port in a Storm: Cryptocurrency Safe-havens during the COVID-19 Pandemic." *Economics Letters* 194: 109377. doi:10.1016/j.econlet.2020.109377.

Corbet, S., G. Hou, Y. Hu, and L. Oxley. 2020b. "The Influence of the COVID-19 Pandemic on Asset-price Discovery: Testing the Case of Chinese Informational Asymmetry." *International Review of Financial Analysis* 72: 101560. doi:10.1016/j.irfa.2020.101560.

Corbet, S., G. Hou, Y. Hu, L. Oxley, and D. Xu. 2021. "Pandemic-related Financial Market Volatility Spillovers: Evidence from the Chinese COVID-19 Epicentre." *International Review of Economics & Finance* 71: 55–81. doi:10.1016/j.iref.2020.06.022.

Corbet, S., Y. Hou, Y. Hu, B. Lucey, and L. Oxley. 2020c. "Aye Corona! the Contagion Effects of Being Named Corona during the COVID-19 Pandemic." *Finance Research Letters* 38 ,101591.

Doornik, J. A., and H. Hansen. 2008. "An Omnibus Test for Univariate and Multivariate Normality." *Oxford Bulletin of Economics and Statistics* 70: 927–939. doi:10.1111/j.1468-0084.2008.00537.x.

Forbes, K. J., and R. Rigobon. 2002. "No Contagion, Only Interdependence: Measuring Stock Market Comovements." *The Journal of Finance* 57 (5): 2223–2261. doi:10.1111/0022-1082.00494.

Funke, M., and A. Tsang. 2020. "The People's Bank of China's Response to the Coronavirus Pandemic: A Quantitative Assessment." *Economic Modelling* 93: 465–473. doi:10.1016/j.econmod.2020.08.018.

Furceri, D., S. Kilic Celik, J. Jalles, and K. Koloskova. 2021. "Recessions and Total Factor Productivity: Evidence from Sectoral Data." *Economic Modelling* 94: 130–138. doi:10.1016/j.econmod.2020.09.025.

Jiang, G., C. M. Lee, and H. Yue. 2010. "Tunneling through Intercorporate Loans: The China Experience." *Journal of Financial Economics* 98 (1): 1–20. doi:10.1016/j.jfineco.2010.05.002.

Lahmiri, S., and S. Bekiros. 2020. "The Impact of Covid-19 Pandemic upon Stability and Sequential Irregularity of Equity and Cryptocurrency Markets." *Chaos, Solitons and Fractals* 138: 109936. doi:10.1016/j.chaos.2020.109936.

Liu, Q., and Z. J. Lu. 2007. "Corporate Governance and Earnings Management in the Chinese Listed Companies: A Tunneling Perspective." *Journal of Corporate Finance* 13 (5): 881–906. doi:10.1016/j.jcorpfin.2007.07.003.

Luo, J., and Q. Zhang. 2020. "Risk Contagions between Global Oil Markets and China's Agricultural Commodity Markets under Structural Breaks." *Applied Economics* 53 (5), 628-649.

Mardia, K. V. 1970. "Measures of Multivariate Skewness and Kurtosis with Applications." *Biometrika* 57 (3): 519–530. doi:10.1093/biomet/57.3.519.

Matkovskyy, R., and A. Jalan. 2019. "From Financial Markets to Bitcoin Markets: A Fresh Look at the Contagion Effect." *Finance Research Letters* 31: 93–97. doi:10.1016/j.frl.2019.04.007.

Sharif, A., C. Aloui, and L. Yarovaya. 2020. "Covid-19 Pandemic, Oil Prices, Stock Market, Geopolitical Risk and Policy Uncertainty Nexus in the Us Economy: Fresh Evidence from the Wavelet-based Approach." *International Review of Financial Analysis* 70,101496.

Umar, Z., D. Kenourgios, and S. Papathanasiou. 2020. "The Static and Dynamic Connectedness of Environmental, Social, and Governance Investments: International Evidence." *Economic Modelling* 93: 112–124. doi:10.1016/j.econmod.2020.08.007.

Wen, F., L. Xu, G. Ouyang, and G. Kou. 2019. "Retail Investor Attention and Stock Price Crash Risk: Evidence from China." *International Review of Financial Analysis*. 65 cited By 77 10.1016/j.irfa.2019.101376

Yamaka, W., P. Tarkhamtham, P. Maneejuk, and S. Sriboonchitta. 2018. "A Regime Switching Skew-distribution Model of Contagion." *Studies in Computational Intelligence* 808: 439–450.