International Review of Economics and Finance 79 (2022) 302–309

Contents lists available at ScienceDirect

International Review of Economics and Finance

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

Stock market contagion during the COVID-19 pandemic in emerging economies

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ARTICLE INFO

JEL classification:
F15
F32
G1
G15

Keywords:
COVID-19
Financial market
Emerging markets
China
Copula
Cross-quantilograms

ABSTRACT

The purpose of this paper is to examine the connected dynamics of the affected Asian financial markets and global financial market in relation to the outbreak of the coronavirus (COVID-19) pandemic. We particularly examine the temporal dependence and connectedness of the affected markets with the global financial market by using the time-varying dependence approach in a time-frequency space under COVID-19. Our findings indicate a strong, positive dependence among the investigated markets' due to the outbreak of COVID-19. In addition, we report an increased tendency of co-movements over the higher horizon which is documented by COVID-19. These findings are of significant interest for market participants, policymakers, and international investors.

1. Introduction

The outbreak of coronavirus (COVID-19), which originated from Wuhan (Hubei region of China), is now recognized as a pandemic and has caused significant uncertainty and distress in the financial and economic markets of the world economy (Chinazzi et al., 2020). Within a span of three months since the first registered case, the number of cases increased to well over one million in more than 200 affected countries around the world as of April 6, 2020 (WHO, 2020a). Several industries – airlines, travel and tourism, hotels – have encountered great challenges in sustaining their business models. The COVID-19 is considered highly contagious and has caused significant uncertainty, the consequences of which are apparent and have resulted in additional stress on financial markets and the global economy. Furthermore, the price volatility in the financial markets of major affected countries has considerably increased; thereby triggering spillovers in the global financial and commodity markets and leading to a significant decline in global indexes during the same day (the Black Monday).

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https://doi.org/10.1016/j.iref.2022.02.028
Received 8 April 2020; Received in revised form 2 February 2021; Accepted 12 February 2022
Available online 15 February 2022

Considering the current context, this paper investigates the variations in the financial market connectedness[1] structure of the major affected regions, namely, China, Hong Kong, Japan, and South Korea, with the world financial index. In particular, we investigate the following unanswered questions: first, we analyze how the financial market connectedness of the affected regions vary with the global financial market index. Second, we evaluate whether COVID-19 is a new source of financial contagion.

The relationship between the stock markets of developing countries and the world has attracted significant attention over the last decade (Al Nasser & Hajilee, 2016; Badshah et al., 2018; Bekaert & Harvey, 2014; Hattori et al., 2016; Yavas & Dedi, 2016). However, the significant decline in the financial markets of these countries due to the outbreak of COVID-19 has raised concern among market participants and policymakers regarding the connectedness of these markets and the global financial market index in the context of COVID-19.

There are several sources that contribute positively to the increased volatility in the financial markets, which may range from market uncertainty to general economic conditions. In addition to those, major macroeconomic announcements may also contribute to increased volatility and connectedness dynamics among the financial markets. In this regard, Onan et al. (2014) reported an asymmetric impact of good and bad volatility on the fear index (VIX), whereas several recent studies examined the impact of Economic Policy Uncertainty (EPU) on the financial risk (Li & Zhong, 2019; Mei et al., 2018; Tiwari et al., 2019).

We contribute to the literature by evaluating the temporal and spectral connectedness dynamics of major affected regions with the global financial index. Our findings indicate strong temporal and spectral co-movements among the affected financial markets with the global financial markets due to the outbreak of COVID-19. Furthermore, we report strong directionality from the global financial markets to the affected financial markets in the extreme lower and the upper quantiles of the return distributions. This indicates that COVID-19 may become a new source of financial contagion.

The rest of the paper is structured as follows: Section 2 presents the data and methodology; Section 3 presents the empirical findings; Section 4 concludes.

2. Data and methodology

We used several approaches to examine the temporal and spectral connectedness among financial markets of the affected countries and the global financial market. Specifically, to capture the asymmetric dependence structure, we used the time-varying Dynamic Conditional correlation (DCC)-Student-t copula method. Due to COVID-19, the market sentiment changes significantly and the trading dynamics of market participants operating across different frequencies have changed. To capture the heterogeneous behavior of market participants, we employed a wavelet coherence approach. Based on the stochastic properties presented in Table 1, the financial markets are negatively skewed and exhibit leptokurtic distribution. Therefore, to capture the extreme-level static and time-varying connectedness, we incorporated cross-quantilograms. We briefly examine the employed frameworks below.[2]

We follow a two-step maximum likelihood procedure to estimate copula parameters (Joe, 1997; Joe & Xu, 1996). In the first step, we estimate the parameters of univariate marginal distribution models as:

$$\log \sigma_t^2 = \kappa + \sum_{i=1}^{P} \beta_i \log \sigma_{t-i}^2 + \sum_{j=1}^{Q} \alpha_j \left[\frac{|\varepsilon_{t-j}|}{\sigma_{t-j}} - E\left\{ \frac{|\varepsilon_{t-j}|}{\sigma_{t-j}} \right\} \right] + \sum_{j=1}^{Q} \xi_j \left(\frac{\varepsilon_{t-j}}{\sigma_{t-j}} \right) \tag{1}$$

where κ, α_j, β_i and ξ_i correspond to the intercept, ARCH, GARCH, and leverage effects, respectively, of the variance equation. σ_{t-1}^2 refers to the lagged conditional variances; the term in $[\cdot]$ captures the magnitude of past standardized innovations, and the past standardized innovations are captured in $\left(\frac{\varepsilon_{t-j}}{\sigma_{t-j}}\right)$. For $\xi_j < 0$, the future conditional uncertainty will increase asymmetrically following a negative and positive shock. In the second step, we estimate time-varying DCC-Student-t copula parameters by utilizing the standardized residuals from the marginal distribution framework and converted it into uniform marginals. The multivariate case of Student-t copula may be expressed as:

$$C_{d,\rho}(u_1, \ldots, u_n) = t_{d,R}\left(t_d^{-1}(u_1), \ldots, t_d^{-1}(u_n)\right) \tag{2}$$

$$\int_{-\infty}^{t_d^{-1}(u_1)}, \ldots, \int_{-\infty}^{t_d^{-1}(u_n)} \frac{\Gamma\left(\frac{d+n}{2}\right)|\rho|^{-\frac{1}{2}}}{\Gamma\left(\frac{d}{2}\right)(\pi v)^{\frac{n}{2}}} \left(1 + \frac{1}{d} z^T \rho^{-1} z\right)^{-\frac{d+n}{2}} dz_1, \ldots, dz_n, \tag{3}$$

where d, t_d^{-1} and $t_{d,\rho}$ represent the degrees of freedom, inverse of univariate t distribution, and multivariate t distribution with ρ matrix, respectively, d refers to the degrees of freedom, and ρ corresponds to positive definite dispersion or scatter matrix.

To examine the time-frequency connectedness among the underlying series, we used the wavelet coherence approach. The wavelet

[1] The words "contagion" and "connectedness" are used interchangeably in this paper. We are thankful to an anonymous referee for highlighting this.

[2] For detailed overview of the employed frameworks, we refer the interested readers to Han et al. (2016); Patton (2006) and Torrence and Webster (1999).

Table 1
Descriptive statistics.

	Mean	SD	SR	Max	Min	Skew	Kurt	J – B	Q(5)	$Q^2(5)$	ARCH
Panel A: (18/1/2018–31/12/2020)											
SHANGHAI	0.000	0.191	−0.053	0.056	−0.080	−0.620	8.374	976***	24***	26***	22***
H-SENG	−0.054	0.195	−0.329	0.049	−0.057	−0.370	5.332	192***	18***	168***	94***
NIKKEI	0.047	0.197	0.189	0.077	−0.063	−0.137	8.867	1107***	23***	495***	206***
KOREA	0.044	0.193	0.173	0.083	−0.088	−0.312	12.828	3111***	51***	942***	371***
WORLD	0.066	0.193	0.292	0.084	−0.104	−1.472	22.509	12489***	226***	912***	296***
Panel B: (18/1/2018–31/12/2019)											
SHANGHAI	−0.059	0.185	−0.371	0.054	−0.057	−0.363	6.607	288***	26***	37***	33***
H- SENG	−0.058	0.175	−0.390	0.041	−0.053	−0.304	4.523	57***	11***	16***	23***
NIKKEI	−0.002	0.163	−0.075	0.038	−0.051	−0.826	6.615	336***	15***	54***	60***
KOREA	−0.072	0.132	−0.620	0.035	−0.045	−0.702	5.601	186***	21***	18***	18***
WORLD	0.039	0.116	0.248	0.030	−0.032	−0.601	5.362	149***	27***	85***	47***
Panel C: (01/01/2020–31/12/2020)											
SHANGHAI	0.115	0.202	0.520	0.056	−0.080	−1.025	10.837	711***	12***	7**	6**
HSENG	−0.046	0.228	−0.244	0.049	−0.057	−0.414	5.294	64***	20***	103***	52***
NIKKEI	0.144	0.250	0.536	0.077	−0.063	0.209	7.687	240***	28***	208***	92***
KOREA	0.270	0.276	0.942	0.083	−0.088	−0.287	8.610	344***	24***	298***	131***
WORLD	0.120	0.290	0.381	0.084	−0.104	−1.242	12.899	1128***	131***	264***	92***

Notes. The annualized values of mean and standard deviation are presented. SR represents the Sharpe ratio and J—B represents the test-statistics from Jarque-Bera normality test. Q(5) and $Q^2(5)$ represent the test-statistics from the Ljung-Box test for serial correlation in returns and squared returns with 5 lags. ARCH(5) correspond to the test-statistics from ARCH test. *** and ** indicate the rejection of null-hypothesis at the 1% and 5% significance level, respectively.

coherence is useful in exploring the relationship among the assets and provides an overview of the overall connectedness structure among the underlying series in the time-frequency space (Grinsted et al., 2004; Torrence & Webster, 1999). The wavelet coherence among the assets may be defined as:

$$\varphi_{x,y}(s) = tan^{-1}\left(\frac{\Im\{s^{-1}W_{x,y}(\tau,s)\}}{\Re\{s^{-1}W_{x,y}(\tau,s)\}}\right), \quad \varphi_{x,y} \in [-\pi,\pi], \tag{4}$$

where $\Im$ and $\Re$ are the smoothed imaginary and real operators, respectively. The phase difference is represented by the black arrows. The zero phase indicates that the two processes are interlinked at a specified frequency. The direction of arrows ($\leftarrow$ ($\rightarrow$)) suggest that the two series are anti-phase (in-phase) or negatively (positively) interconnected. The direction of arrows ($\swarrow$ *and* $\nearrow$) implies that the series y leads x, while the arrows ($\searrow$ *and* $\nwarrow$) implies that the x leads y (Torrence & Webster, 1999).

To evaluate the variations in the connectedness across different quantiles of the return distribution, we utilize a cross-quantilogram (CQC) approach proposed by Han et al. (2016). Let $x_t = (x_{1t},\ x_{2t})^T \in \mathbb{R}^{d_1} \times \mathbb{R}^{d_2}$ and $y_t = (y_{1t}, y_{2t})^T \in \mathbb{R}^2$, and we define the conditional quantile and distribution function as $q_{i,t}(\tau_i) = inf\ \{v\ : F_{(y_i|x_i)}(v|x_{it}) \geq \tau_i\}$ and $F_{(y_i|x_i)}(\cdot|x_{it})$ for any $\tau_i \in (0,\ 1)$. We can then define the cross-quantilogram as the cross-connectedness of various quantiles as:

$$\rho_\tau(k) = \frac{E\left[\psi_{\tau_1}(y_{1,t} - q_{1,t}(\tau_1))\psi_{\tau_2}(y_{2,t-k} - q_{2,t-k}(\tau_2))\right]}{\sqrt{E\left[\psi^2_{\tau_1}(y_{1,t} - q_{1,t}(\tau_1))\right]}\sqrt{E\left[\psi^2_{\tau_2}(y_{2,t-k} - q_{2,t-k}(\tau_2))\right]}} \tag{5}$$

where k represents the lead-lag to time t. Following Han et al. (2016), we evaluate the null-hypothesis of no conditional dependence ($H_0 : \rho_\tau(1) = \ldots = \rho_\tau(p) = 0$) against an alternative hypothesis ($H_1 : \rho_\tau(k) \neq 0,\ \forall k \in \{1\ldots\ldots p\}$) by utilizing a Box-Ljung test for statistical inference as:

$$\widehat{Q}_\tau(p) = T(T+2)\sum_{k=1}^{p}\frac{\widehat{\rho}^2(k)}{T-k}. \tag{6}$$

The employed methodologies enable us to, first, disentangle the asymmetric connectedness structure among the assets due to the outbreak of COVID-19. Second, the outbreak of COVID-19 lead to the heterogeneous preference of market participants. We captured this heterogeneity by using wavelet coherence approach that enabled us to unravel the investment behavior of the market participants across various investment horizons. Finally, we captured the skewed and leptokurtic distribution behavior among the underlying countries by utilizing the cross-quantilograms. The CQC enabled us to provide an overview of the development of dependence structure between median and extreme quantiles of the return distribution.

We incorporate daily data spanning from January 2018 to December 2020. The underlying data was collected from Thomson Reuters DataStream. We estimated the logarithmic returns for each series at time t and $t-1$ as $r_{i,t} = \ln(P_{i,t}) - \ln(P_{i,t-1})$. Table 1 presents the descriptive statistics for the affected regions and the global stock market index. The mean annualized return varies from

0.00% (Shanghai) to 6.6% (World) for the full sample estimates. The return for the pre-crisis period (period before the first registered case) fluctuates from −7.2% (Korea) to 3.9% (World). For the crisis-period, we observe that the average return varies from −4.6% (Hang Seng) to 27.0% (Korea). The World financial index mean annualized return of 12.0% during the 2020. Fig. 1 shows the development of logarithmic price series of the affected countries and the global financial market index. The graphical output demonstrates that the Nikkei and Korea financial indices follows a similar trend as that of the global financial index throughout the sample

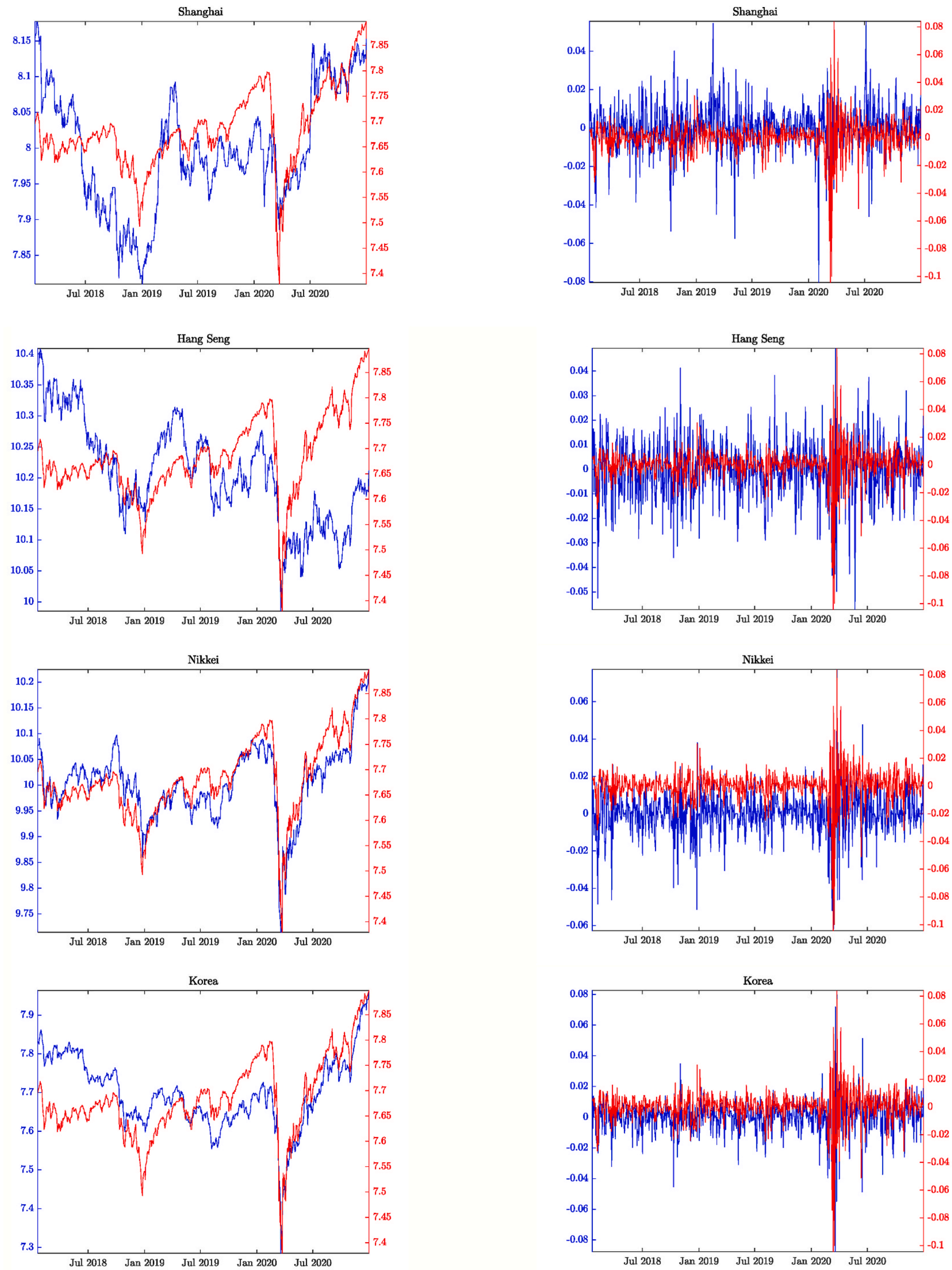

Fig. 1. Development of price and return series. Notes. The red and blue lines represent the development of logarithmic price and return series of global financial index and individual financial indexes, respectively. (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)

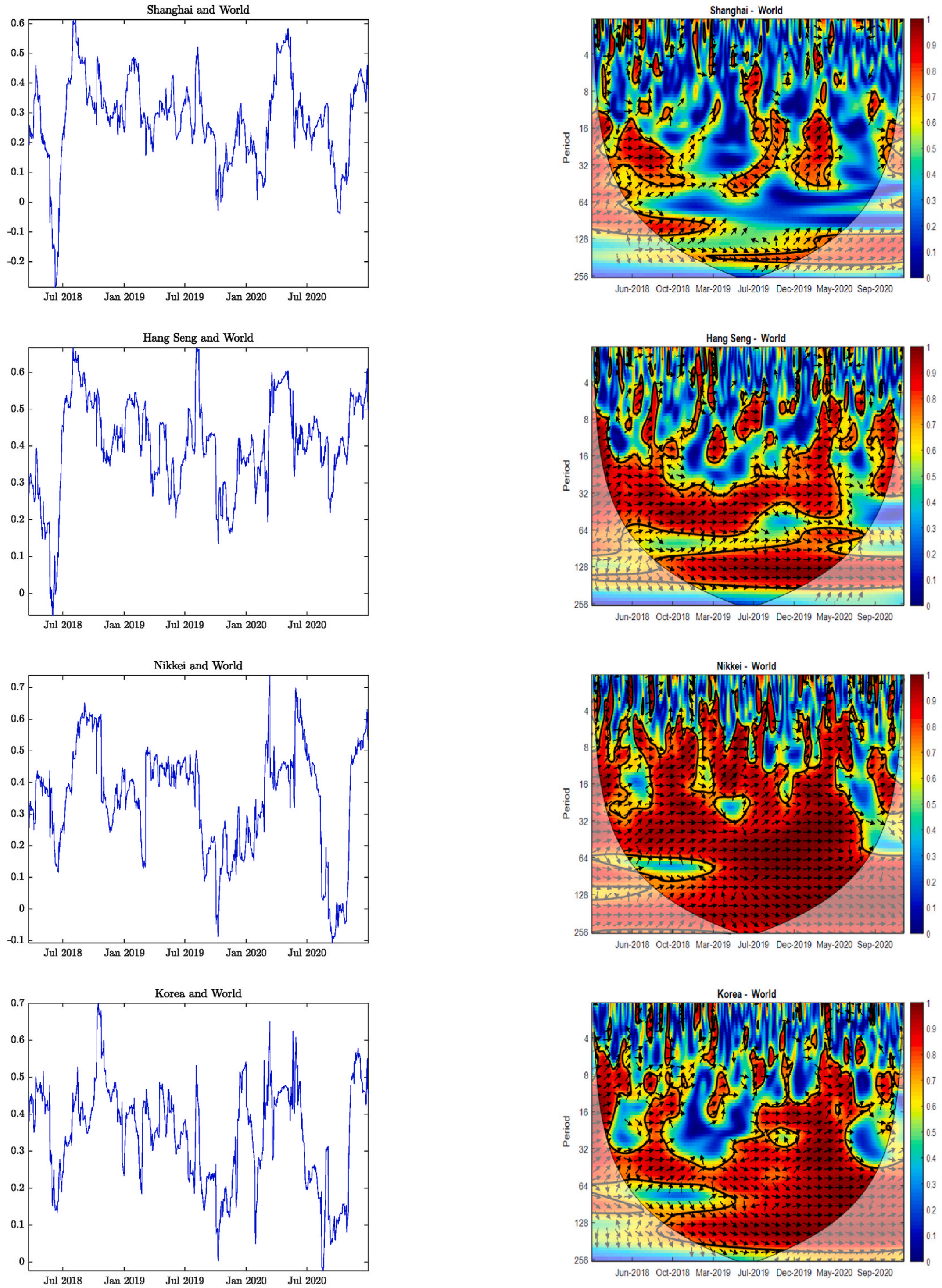

Fig. 2. Time-varying DCC-Student-t copula parameter and wavelet coherence. Notes. This figure portrays the temporal development of dependence structure and the time-frequency connectedness between global financial index and individual stock indexes. The blue line represent the development of time-varying asymmetric dependence parameter from DCC-Student-t copula. The direction of arrows (← (→)) suggest that the two series are anti-phase (in-phase) or negatively (positively) interconnected. The direction of arrows pointing (↙ *and* ↗) implies that the series *y* (World) leads *x* (individual indices), while the arrows (↘ *and* ↖) implies that the *x* leads *y* (Torrence & Webster, 1999). (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)

period. Furthermore, it is noteworthy that Shanghai and Hang Seng have received a considerably less shock due to the outbreak as opposed to Nikkei and Korea. This may be attributed to fact that these markets are partially or fully controlled and regulated. In contrast, both Korea and Nikkei are free float and more integrated with the financial markets in the rest of the world, resulting in a significant decline of these indices during the first wave of COVID-19. However, the indices increased significantly with the stability in the pandemic uncertainty. In addition, the episodes of volatility clustering is apparent in all the underlying markets with the declaration of COVID-19 as pandemic by the WHO (WHO, 2020b), suggesting the utilization of marginal distributional framework to capture dependence.

3. Empirical analysis and findings

In this section, we first evaluate the dependence dynamics among the affected countries and the global financial index using time-varying DCC-Student-t copula method. It is evident from Fig. 2 that the dependence among the affected regions with the global financial index is characterized by time-varying dependence. Furthermore, the dependence structure varies from weak negative to strong positive. It is noteworthy that the connectedness between underlying financial markets with the global financial index increases significantly with the declaration of COVID-19 as pandemic. The interconnectedness between markets remains significantly high between February 2020 to May 2020. The connectedness structure between the markets declines significantly during June 2020 to July 2020. This may be attributed to the strict contingency measures and stimulus packages to tackle the pandemic uncertainty. However, the connectedness increases significantly during October 2020 and remain persistently high towards the end of sample. This may be attributed to the easing of contingency measures, resulting in increased connectedness among the assets. This may be characterized as the "second wave" of COVID-19.

Fig. 2 examines the time-frequency connectedness among the affected financial markets and the global financial index. Similar to the temporal dependence parameter from copula framework, we observe positive dependence between global financial index and the Shanghai from December 2019 to May 2020. However, from May 2020 onwards, the connectedness is primarily characterized over the smaller frequencies (short-term horizon. This may be attributed to the strict contingency measures undertaken by the Chinese government to cope with the COVID-19. However, the financial markets of Hang Seng, Nikkei, and South Korea exhibits significant positive connectedness over frequencies higher than 8 days, indicating an increased co-movement tendency with the global financial index. These findings imply that over the medium-term horizon (one to two-month period) there may be a further increase in connectedness among the underlying assets. Similar to DCC-Student-t copula, the statistically significant and positive contours from August 2020 onwards signifies the strengthening of the "second wave" of COVID-19. This indicates the relevance and the importance of undertaking a time-frequency measure to evaluate connectedness among the assets. The standard time series models ignore information embedded in the frequency domain of the underlying time series. However, the financial and commodity markets comprise

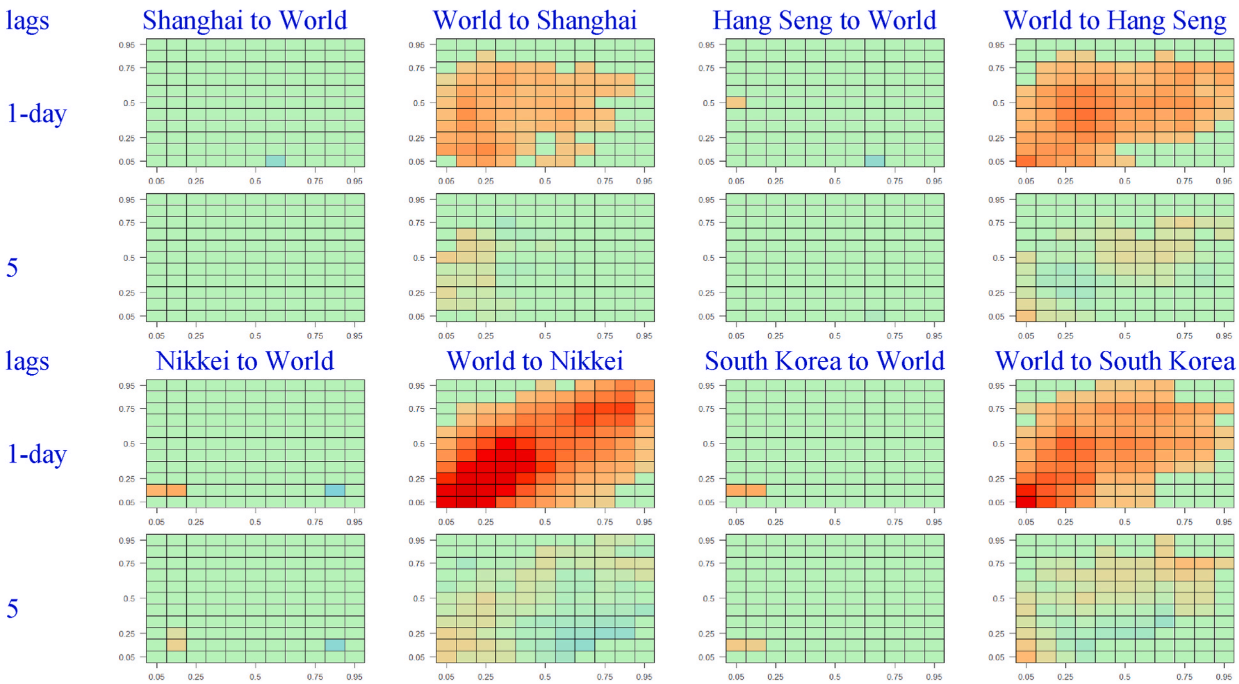

Fig. 3. Cross-quantilogram between affected countries and world. Notes. The figure displays the cross-quantile dependence among the global financial indexes and the affected Asian countries. The CQC is estimated by incorporating Eq. (5) and the statistical significance is determined by employing Ljung-Box test as specified in Eq. (6). The insignificant correlation is set to zero and only the significant directional dependence is reported. The lags correspond to daily and weekly variations, respectively. The scale represents the intensity and direction of connectedness structure.

of agents that tend to operate at various frequency horizons.

Fig. 3 present the cross-quantilograms among the world financial index and the financial indexes of the affected regions. Interestingly, with regard to predictability, we observe positive directional predictability from the world financial index to the affected regions across all quantiles of the return distribution. This result is not unexpected as the world financial index captures the performance of overall global financial markets and thus may exhibit strong predictive power over the regional financial market indexes. However, it is noteworthy that Fig. 3 provide the quantile connectedness among the series in a static setting. Therefore, to evaluate the time-varying quantile-dependence among the underlying assets, we utilized the time-varying cross-quantilograms.

Fig. 4 presents the output of time-varying cross-quantilograms. Interestingly, we observed moderate dependence among the underlying series in the extreme upper and lower quantiles of the return distributions, which indicated an increased tendency of co-movement in the extreme market conditions. The increased tendency may be attributed to the asymmetric variations (sudden increase/decrease) in the connectedness dynamics in the extreme upper [0.95–0.95] and lower [0.05–0.05] quantiles of the return distributions as compared to the median (normal state) [0.5–0.5] quantile. This is advantageous to undertake as a large number of standard frameworks (see for example, copulas, dynamic conditional correlations, among others) provide an estimation of connectedness dynamics among the underlying series based on normal state. However, under the extreme event condition (global financial crisis, COVID-19), it is interesting to look carefully the bearish or bullish market rather than the normal market condition. This may be attributed to the higher risk observed by the market participants in these affected markets and the preference of investors to divert toward less uncertain assets.

4. Conclusion

This paper evaluated the temporal and spectral dependence and quantile-based connectedness dynamics of the global financial

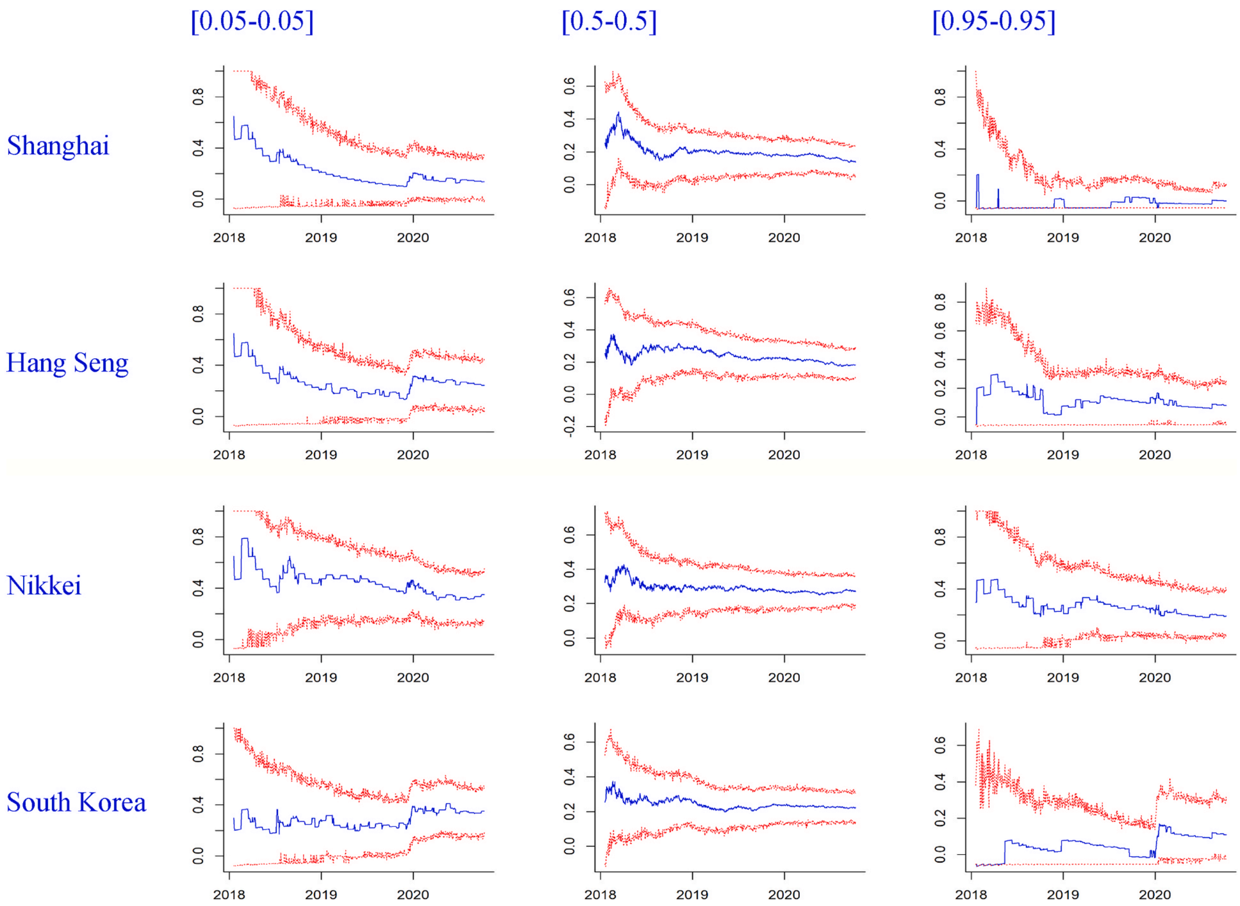

Fig. 4. Time-varying development of cross-quantilogram among the world and the affected markets. Notes. The recursive cross-quantilogram are estimated by setting the length of the first window to 30-days that moves forward on a daily basis. The columns from left-to-right corresponds to recursive CQC estimates when both series are at the lower (5%), median (50%), and upper (95%) quantiles, respectively. The red lines correspond to the no-predictability of the null-hypothesis at 95% confidence interval, while the blue line represent the time-varying CQCs in the recursive subsample. The confidence interval is derived from a bootstrap procedure of 1000 iterations at each step of the recursive subsample. (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)

market index and the affected Asian financial markets due to the outbreak of the coronavirus (COVID-19) pandemic. We utilized time-varying DCC-Student-t copula, wavelet coherence, and cross-quantilograms to evaluate the variation in dependence structure and predictability.

Our findings revealed an increased overall connectedness among the underlying assets due to the outbreak of COVID-19. Additionally, we report that the dependence among the underlying assets heightens with the increase in frequency horizons. Specifically, over the period of one to two months, the connectedness structure among the underlying assets tends to increase. Finally, our findings indicate an increased directional predictability in the extreme lower and upper tails of the quantile distribution, reflecting the impact of COVID-19 on the connectedness structure.

These findings are of significant interest for policymakers, market participants, and international investors. Policymakers should devise a roadmap to disentangle the impact of uncertainty on the respective financial markets. Market participants and international investors should accommodate the extreme market conditions in their models to formulate relevant and appropriate portfolio management decisions.

Author statement

Gazi Salah Uddin: Conceptualization, Project administration, Writing – review & editing **Muhammad Yahya:** Formal analysis, Methodology, Software, Writing - original draft, Writing - review & editing **Gour Gobinda Goswami:** Writing - review & editing. **Brian Lucey** Writing - review & editing. **Ali Ahmed** Conceptualization, Writing – review & editing, Project administration.

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