# The outbreak of COVID-19 and stock market liquidity: Evidence from emerging and developed equity markets

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A B S T R A C T

The outbreak of the novel corona virus has heightened concerns surrounding the adverse financial effects of the outbreak on stock market liquidity and economic policies. This paper contributes to the emerging strand of studies examining the adverse effects of the virus on varied aspect of global markets. The paper examines the causality and co-movements between COVID-19 and the aggregate stock market liquidity of China, Australia and the G7 countries (Canada, France, Italy, Japan, Germany, the UK and the US), using daily three liquidity proxies (Amihud, Spread and Traded Value) over the period December 2019 to July 2020. Our empirical analysis encompasses wavelet coherence and phase-differences as well as a linear Granger causality test. Linear causality test results suggest that a causal relationship exists between the number of cases of COVID 19 infections and stock market liquidity. To quantitatively examine the degree of causality between COVID-19 outbreak and stock market liquidity, we employ the continuous wavelet coherence approach with results revealing the unprecedented impact of COVID-19 on stock market liquidity during the low frequency bands for countries that were hard hit with the COVID-19 outbreak, i.e., Italy, Germany, France, the UK and the US. Further, evidence shows that there is a heterogeneous lead-lag nexus across scales for the entire period of the study.

## 1. Introduction

Since early 2020, the global financial markets have been shaken by the outbreak of COVID-19. Due to the virus's huge global impact, the emergence of several studies on the financial and economic effects of COVID-19 has been witnessed in finance literature (e. g., Zhang, Hu, & Ji, 2020; Tiwari, Abakah, Dwumfour, & Gil-Alana, 2020; Abakah, Caporale, & Gil-Alana, 2021; Caporale, Kang, Spagnolo, & Spagnolo, 2021). Previous literature has considered the impact of financial, environmental and/or health crises on macroeconomic indicators such as inflation, interest rates, unemployment, just to mention a few (Salisu, Ogbonna, & Adediran, 2021) as well as on some firm specific and financial indicators such as stock returns, volatilities (Okorie & Lin, 2020; Sharif, Aloui, & Yarovaya, 2020) and investment funds (Mirza, Naqvi, Rahat, & Rizvi, 2020). Other studies commenting on the eruption of Covid19, showed the reaction of commodity markets, minerals, stock markets and cryptocurrencies to the pandemic (Bai et al., 2021; Corbet, Hou, Hu, Larkin, & Oxley, 2020; Haroon and Rizvi, 2020a, 2020b; Zhang et al., 2020). For example, Al-Awadhi, Alsaifi, Al-Awadhi, and Alhammadi (2020), Mishra, Rath and Dash (2020) concentrate on the performance of stocks in China and India, supporting the

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existence of significant impacts of Covid19 on the performance of stocks. Zaremba, Aharon, Demir, Kizys, and Zawadka (2021) document the effect of effective government responses on the volatility of bond markets during the Covid19 pandemic. Their findings were congruent with earlier studies that stringent measures and economic support reduced the volatility of financial assets as were those of Phan and Narayan (2020) for travel and leisure stock markets. Ashraf (2020a) also studies the reaction of stock markets to Covid19 and finds a reduction in the returns of stocks to a one percent increase in the growth of confirmed cases. Thus, the Covid-19 induced global crisis has left an unforgettable dent, just like the 2007/08 crisis, in the global economic and financial markets.

Stock market liquidity is essential for economic growth and financial stability during extreme volatile conditions. Butler, Grullon, and Weston (2005) find that higher levels of liquidity lead to a decline in the cost of equity capital which can alleviate a firm's funding constraints and further contribute to a firm's financial resilience to the outbreak of COVID-19 pandemic. Moreover, given that liquidity permits the immediate recognition of a gain or loss, the need to investigate its features under extreme volatile market conditions cannot be ignored. Additionally, market participants, including fund and portfolio managers, regulators and policy makers have constantly been monitoring liquidity to improve decision making in their quest to safeguard economic growth and financial stability during the outbreak of the novel coronavirus. Interestingly, even though several emerging studies on the effects of the COVID-19 pandemic on the financial markets have been analyzed from different perspectives, leading to a comprehensive emerging literature (Ashraf, 2020a; Goodell, 2020; Insaidoo, Arthur, Amoako, & Andoh, 2021; Takyi & Bentum-Ennin, 2021; Tiwari, Séraphin, & Chowdhary, 2021; Topcu & Gulal, 2020), the literature is still limited since there are several questions yet to be identified and explored on the financial effects of the COVID-19 pandemic. The objective of the study is to contribute to the extant literature on COVID-19 and stock markets by investigating the impact of the COVID-19 outbreak on stock market liquidity around the world focusing on emerging and developed equity markets.

Our pursuit to determine the impact of the Covid19 pandemic on stock trading activities follows theoretical arguments that the behavior of financial securities, for example stocks in terms of returns and volatilities as well as investor behavior, are influenced by macroeconomic events and news that can directly or indirectly affect trade and returns (Haroon and Rizvi, 2020a, 2020b; Salisu, Sikiru, & Vo, 2020). Several studies have considered the effect of macroeconomic indicators on stock trading activities (Ashraf, 2020a; Baker, Bloom, Davis, & Terry, 2020; Corbet et al., 2020; Le, Abakah, & Tiwari, 2020; McKibbin & Fernando, 2020; Okorie & Lin, 2020; Topcu & Gulal, 2020), however, very few have assessed the impact of extreme global conditions on stock trading activities. The Covid19 pandemic saw a halt in business activities, affecting business performance and consequently the dynamics of stock markets (Bloom, 2009; Lam, Zhang, & Zhang, 2020; Okorie & Lin, 2020). Literature suggests that financial market trading activities and investor behavior are affected by global crises and that the recent pandemic is not an exception (Brunnermeier, 2009; Kaplanski & Haim Levy, 2010). Due to the ease of convertibility of financial assets, specifically stocks into cash and vice versa, defining the liquidity of stocks is extremely crucial in periods of crises and remains prominent in decision-making regarding choice of assets on the part of investors. Liquidity premiums are mostly required by investors who hold assets in less liquid assets thus influencing the cost of equity and firm value (Amihud & Mendelson, 1986; Butler et al., 2005; Fang, Noe, & Tice, 2009). This being an important feature of financial markets, we assess how the news of Covid19 influences the trading activities of financial assets, unambiguously the liquidity stocks of markets of advanced and emerging economies. We ask whether the Covid19 pandemic affected stock market liquidity due to investors perceived choice of holding more liquid assets in periods of increased uncertainty and even more so during pandemics. Stock liquidity is indicative of the flow of capital and some studies support its association to the degree of market efficiency (Chordia, Roll, & Subrahmanyam, 2008). Given the importance of the liquidity of stock in market efficiencies and firm value, there is a need to examine how this vital characteristic of equity markets is impacted by a global pandemic that halted activity in the greater part of the global economy. Tran, Hoang, and Tran (2018) report on stock liquidity commonality during the 2009 global financial crisis and how that affects realized stock returns of international equity returns (see Dang & Nguyen, 2020). To the best of our knowledge, studies of stock liquidity and the impacts of the Covid19 have been less represented or examined in literature (Adrian and Natalucci, 2020).

An important question that needs to be addressed is regarding the mechanism of the impact of the COVID 19 pandemic on stock market liquidity, and to distinguish the impact of the epidemic on stock liquidity from the impact of stock returns. Following the outbreak of the COVID-19 virus and its associated issues that forced governments to implement several policy responses among other measures, at least three mechanisms have been identified through which the outbreak of COVID-19 may affect the liquidity of equity markets. The first mechanism is described as the "infrastructure channel'. The closure of workplaces during the outbreak of COVID-19 in order to curb the spread of the virus may have distorted the decision processes of most financial institutions, thereby prohibiting quick trading and swift reactions. Since most financial firms were physically closed, traders may not have been able to trade or transact business in situations where there was lack of proper electronic infrastructure or regulatory frameworks. In cases where a significant part of the trading is automated and the economy is controlled digitally, the role of these factors would be, at least, partly reduced. In particular, the impact may be potentially stronger in emerging equity markets than in developed markets (Ersan & Ekinci, 2016; Glantz & Kissell, 2013). On the other hand, even if workplaces were not actually closed, other "softer" measures may have had an indirect impact. For example, internal travel restrictions may result in disruptions for commuters, and school closures require parents to stay home leading, in turn, to significant absenteeism (Chen, Guo, & Huang, 2018; Epstein et al., 2020). The second mechanism is described as the "portfolio channel". Policy responses implemented by governments' signaled variations in the future economy, resulting in the need for portfolio restructuring. Notably, the deteriorating economic conditions may result in changes in cash flow expectations for firms and, thus, portfolio reallocations. Additionally, investors may be less willing to invest their money in risky assets, such as stocks. School or workplace closures may signal a worsening of future household cash flows (Chen et al., 2018; Epstein et al., 2020), which increases the risk premium. Third, market participants can be induced by psychological and behavioral factors. Galai and Sade (2006), Karlsson, Loewenstein, and Seppi (2009), as well as Sicherman, Loewenstein, Seppi, and Utkus (2016), note the "ostrich effect", which suggest that market participants in the wake of bad news are reluctant to follow and monitor their portfolios. Thus, investors may

prefer to simply "put their head in the sand" rather than trade when confronted with a stream of negative news on government restrictions. This may be also amplified by the "information overload" effect (Agnew & Szykman, 2005). Behind this argument is the idea that when a problem is loaded with information and thus is too hard to understand, an easy solution is just to nothing. Additionally, Thaler and Johnson (1990) show that individuals who experience several consecutive periods of losses become more loss-averse and avoid taking additional gambles. Pursuant to this line of thinking, trading activity decreases.

To the best of our knowledge, this is one of the foremost studies to examine the impact of coronavirus outbreak on stock market liquidity. We contribute to the ongoing debate on the effects of COVID-19 pandemic on global financial markets in threefold. First, we extend the literature by providing fresh empirical evidence on the linkages between COVID-19 and stock market liquidity. This study offers a broader perspective on the issue of stock market liquidity and the case count as well as deaths caused by COVID-19, using a modern method of time-series and a multi-country analysis. A significant number of these studies overlook one of the most important characteristics of efficient capital markets during pandemics and periods of increased uncertainties – stock liquidity. Our study focuses on the recent pandemic and its influence on the stock trading activities of Australia, China and the G7 economies. Specifically, we examine the extent to which the outbreak of COVID-19 impacted stock market liquidity across the selected countries. Second, we provide evidence on the effect of the COVID-19 pandemic on international financial markets for international portfolio investors to aid the creation of wealth, portfolio formulation, diversification and trading activities during crisis period similar to other studies on the impact of COVID-19 on financial markets (Ashraf, 2020a; Goodell, 2020; Insaidoo et al., 2021; Takyi & Bentum-Ennin, 2021; Tiwari et al., 2021; Topcu & Gulal, 2020). In particular, we chose to concentrate on China, Australia and the countries of the G7 (Canada, France, Italy, Japan, Germany, the UK, and the US) due to the interconnectedness of the stock markets of these economies (see Liu, Gregoriou, & Bo, 2020) and the possible contagion effect of the Covid19 pandemic across these economies (Akhtaruzzaman, Boubaker, & Sensoy, 2020). Further, these economies are deemed to have been the hardest-hit areas by the pandemic and as well possessing some of the most vibrant financial markets in the world. Nevertheless, studies indicate that these economies performed better in terms of the downward effect of the pandemic (Ashraf, 2020b; Baker et al., 2020; Phan & Narayan, 2020; Ramelli & Wagner, 2020). Third, we employ the continuous wavelet (i.e., time–frequency) approach. This approach is adopted as it has the capacity to reveal underlying processes with changing trends, lead-lag interactions and non-stationarity that characterize the behavior of the data being considered. The application of the wavelet method permits us to discover the relations between the incidence of Covid19 and the liquidity that exists in the equity markets of the countries under study. Other econometric approaches render some difficult in identifying such relationships with the efficiency that the wavelet approach offers. Furthermore, the wavelet analysis is characterized as being model-free. This is in contrast to other traditional econometric models that estimate the parameters in only one or at most two time scales. The wavelet approach permits the study of time-series in both the time and frequency domain. The wavelet framework, for these reasons, has considerable advantages over the traditional frequency methods when the time-series under study are non-stationary.

We document several interesting findings. Our results show strong evidence of co-movement between stock liquidity and COVID-19 outbreaks for all countries. However, the causality is strong for countries that recorded high counts of COVID-19 infections and death such as Italy, France, the US and the UK. This is not surprising since the outbreak of the virus increased uncertainty in these economies and may have influenced the investment activities and trading pattern of investors. For countries like Canada, Japan and Australia, we find weak causality at the latter end of our sample period.

The layout of the paper is as follows: Section 2 outlines the literature review; Section 3 accounts for the econometric framework; Section 4 describes the data; Section 5 presents the main empirical findings; Section 6 offers some concluding remarks.

## 2. Literature review

The economic impact of crises, natural disasters, diseases and wars have been recently documented in literature to show adverse effects (Al-Awadhi et al., 2020; Gangopadhyay, Haley, & Zhang, 2010; Goodell, 2020; Ichev & Marinč, 2018; Kowalewski & Śpiewanowski, 2020). The global financial crises of 2008–2009 clearly influenced the performance of the financial assets of major financial markets of developed economies. The interconnectedness of crises and spillover effects on major economic variables have been cited in the literature by, among others, Bekiros (2014), Luchtenberg and Vu (2015), Yarovaya, Brzeszczyński, and Lau (2016) and Su (2020). Comparing the impacts of COVID-19 and the GFC, Shehzad, Xiaoxing, and Kazouz (2020) prove the perilous effect of COVID-19, resulting in global financial crises. The literature on the impacts of COVID-19 spans a wide array of economies more than the 2008/9 GFC which had major effects in the United States and trickled into other economies. Considering the economic impacts of crises, Goodell (2020) points out COVID-19 may have a wider impact on financial sectors across countries.

The stock market reaction to the COVID-19 pandemic has featured quite a lot in recent literature (Baker et al., 2020; Erdem, 2020; Haroon and Rizvi, 2020a, 2020b; Zhang et al., 2020). Several empirical studies consider different aspects of the financial markets and their reaction to the Covid19 pandemic. For example, Al-Awadhi et al. (2020), Li, Strahan, and Zhang (2020), Pavlyshenko (2020) and Sharif et al. (2020) studied the effect of the pandemic on stock returns, Albulescu (2020), Cheng (2020), Onali (2020) studied the volatility of stocks during Covid19 and Haroon and Rizvi (2020a, 2020b) study the liquidity of stocks. Other studies considered the impact of the Covid19 on other asset classes. These studies included bonds (Arellano, Bai, & Mihalache, 2020; He, Liu, Wu, Gu, Zhao, & Yue, 2020; Ji, Liu, Cunado, & Gupta, 2020) commodities (Corbet, Larkin, & Lucey, 2020; Devpura & Narayan, 2020; Narayan, 2020; Umar, Gubareva, Tran, & Teplova, 2021), cryptocurrencies (Corbet et al., 2020; Umar & Gubareva, 2020). Nevertheless, the literature shows varying impacts of Covid19 on financial assets. Evidence from the performance of the US stock market, using the S&P1500, indicate that sectoral stocks such as natural gas, food, healthcare and software recorded positive returns whereas the petroleum, real estate, entertainment and hospitality sectors crashed during the height of the pandemic turmoil (Mazur, Dang, & Vega, 2020).

Lahmiri and Bekiros (2020) report on the diminished stability levels of cryptocurrency markets, increased volatilities with

increased levels of irregularity, similar to that of international equity markets during the COVID-19 pandemic. Corbet et al. (2020) indicate the contagion effect of the recent pandemic and show significant shift of capital from some financial assets to safer commodities and cryptocurrencies though the latter is not clearly seen as a diversifier due to its newness in the financial space (see also Shahzad, Bouri, Roubaud, & Kristoufek, 2020).

Considering, non-financial assets, Akhtaruzzaman et al. (2020) showed the magnitude of increased correlations between financial and non-financial stock returns in China and G7 countries during the COVID-19 outbreak. Their study also shows considerably higher levels of correlations for financial firms, indicating the occurrence of financial contagion transmissions. Chiang (2019) indicate that periods of uncertainties in economic policies were harmful to stock returns when compared to periods of tranquility. Ashraf (2020a) examines the stock markets' response to the COVID-19 pandemic using daily COVID-19 confirmed cases, deaths and stock market returns from 64 countries, and report a decline in returns for increases in cases. Economic policy uncertainty as a result of the COVID-19 pandemic could be seen as a factor behind increased risks and stock market volatilities, thereby affecting liquidity and stock returns. Prior studies on the effects of equally dire global crises, such as the GFC on stock market liquidity, suggest a causal relationship between economic policy uncertainty and stock market liquidity (Dash, Maitra, Debata, & Mahakud, 2019; Yeyati, Schmukler, & Horen, 2008). Tran et al. (2018) suggest that stock market (il)liquidity in times of crisis is somewhat attributable to financial contagion which is characterized by liquidity commonality and flight-to-liquidity (Brunnermeier & Pedersen, 2009). The co-movement of individual assets liquidity with market liquidity known as the liquidity commonality; and shifting of investor choice from less liquid assets to more liquid assets - flight to liquidity, increases the systematic risk and is seen as significant during periods of crises (Rösch & Kaserer, 2013). On the stock liquidity effect from the recent pandemic, Baig, Butt, Haroon, and Rizvi (2020) show significant increases in market illiquidity and volatility with increases in confirmed cases and deaths. Studies have shown that declining trends of stock markets affect the liquidity of stocks during crises as investors exhibit increased levels of risk aversion (Gârleanu & Pedersen, 2007).

Concentration on the G7 countries is a relevant as fundamental economic factors exhibit cross-country associations (Su, 2020), thus the contagion effect of COVID-19 affecting similar economies. Liu et al. (2020) examined the relationship between stock liquidity and stock returns pre, during and post the 2007–2009 financial crises and document a positive association for Germany and the UK, but negative and inconclusive results for China and the US respectively. The countries used in Liu et al. (2020) are, with the exception of China, members of the G7 which are seen to have similar characteristics in their financial architecture. Using time-varying copulas with Markov switching regimes, Ji et al. (2020) showed risk spillovers between the US stock market and the remaining G7 stock markets. With financial market distortions from the COVID-19 pandemic and inconclusive literature on liquidity-returns relations (Lee, 2011), this study ventures to contribute to the literature and policy on the effects of the prevailing pandemic on stock (il)liquidity, which in turn affects efficient capital allocation, portfolio formation and subsequently, returns.

## 3. Empirical methodology

### 3.1. The continuous wavelet methodology

The wavelet transform approach decomposes signals into dilated and translated functions referred to as the mother wavelet u(t). The mother wavelet is expressed as a function of two constructs where one focuses on the time position (s) with the other parameter focuses on the scale of the wavelets. Hence a time series x(t) that has been subjected to the wavelet transform decomposition with reference to the selected mother wavelet is presented in Eq. (1):

$$W_x(\alpha, \tau) = \frac{1}{\sqrt{a}} \int_{-\infty}^{+\infty} x(t)\varphi^*\left(\frac{t-\tau}{a}\right)dt = \int_{-\infty}^{+\infty} x(t)\varphi^*_{a,\tau}(t)dt, \tag{1}$$

where $W_x(\alpha, \tau)$ denotes the influence of the scales while * denotes the influence of the complex conjugate form leading to a two-dimensional surface denoted as $\mathscr{R}(W_x(\alpha, \tau))$.

The wavelet approach adopted in this paper rests on several considerations. Nevertheless, Mallat (1998) posits that the best methodology to consider in examining quantitative information about phase connections that exist between two time series is continuous and complex wavelets. In the literature, the two most referred continuous wavelets are the "Mexican hat" and "Morlet wavelet". High frequency resolution is associated with the Morlet wavelet since its scales and frequencies are very localized. However, for the Mexican hat frequency localisation is poor but has good time localisation.

In this paper, the Morlet wavelet is adopted for the purposes of the study,

$$\varphi(t) = \pi^{-1/4} exp(-i2\pi f_0 t) exp\left(-t/2^2\right).$$

Under the Morlet wavelet, the nexus amid the wavelet scale and the frequency is outlined below $\frac{1}{f} = \frac{4\pi a}{\omega_0 + \sqrt{2 + \omega_0^2}}$ with $\omega_0$ about 2.

For the Morlet wavelet, the studied signal is separated into phase and amplitude since it can be factored into an imaginary and a real part. We write a complex wavelet coefficient $W_x(\alpha, \tau)$, which references its phase $\phi_x(\alpha, \tau)$ and modulus $W_x(a, \tau)$.

We discretised Eq. (1) for time series $\{x_n : n = 1 \ldots N\}$ for practical purposes as shown below:

$$W_x^n(a, t) = \frac{\delta t}{\sqrt{a}} \sum_{n=0}^{N-1} x_n \cdot \varphi^*\left((m-n)\frac{\delta t}{a}\right), \quad m = 1, 2, \ldots, N-1. \tag{2}$$

From Eq. (2), $\delta t$ denotes the uniform step size. Following Torrence and Compo (1998), we explored the expediency presented discrete Fourier transform by discretising the wavelet transform as presented below:

$$W_x^n(a,t) = \frac{\delta t}{\sqrt{a}} \sum_{n=0}^{N-1} \widehat{x}_n \cdot \varphi^*(a\omega_m)e^{i\omega kn\delta t}, \quad m = 0, 1, 2, ..., N-. \tag{3}$$

A set of scales necessary for use in the wavelet transform was obtained using the formula below.

$a_j = a_0 2^{j\delta t}, \quad j = 0, 1, ..., J,$ where $J = \delta j^{-1} \log_2(N\delta t/a_0)$. $a_0$ denotes the least resolvable scales, which is chosen to ensure that the corresponding Fourier period is about $2\delta t$.

Wavelet Power Spectrum, Wavelet Coherency and Phase Difference.

With spectral approaches, we compute the localized wavelet power spectrum as:

$S_x(f, \tau) = |W_x(f, \tau)|^2$..

We employ the wavelet cross spectrum and the wavelet coherence to compute the relation between the two time series that are non-stationary.

The wavelet cross-spectrum employed in this study is given by:

$W_{x,y}(f, \tau) = W_x(f, \tau)W_y^*(f, \tau)$..

**Table 1**
Descriptive statistics of stock liquidity variables.

| Countries | Mean | Std Dev | Q1 | Median | Q3 |
|---|---|---|---|---|---|
| **USA** | | | | | |
| Amihud | 0.0700 | 0.0663 | 0.0228 | 0.0516 | 0.0963 |
| Spread | 0.0154 | 0.0125 | 0.0068 | 0.0110 | 0.0190 |
| Traded Value | 13.0280 | 0.1203 | 12.9441 | 13.0002 | 13.1070 |
| **UK** | | | | | |
| Amihud | 0.0093 | 0.0103 | 0.0019 | 0.0058 | 0.0147 |
| Spread | 0.0241 | 0.0193 | 0.0119 | 0.0175 | 0.0298 |
| Traded Value | 11.8533 | 0.1328 | 11.7727 | 11.8255 | 11.9235 |
| **Italy** | | | | | |
| Amihud | 0.0007 | 0.0007 | 0.0002 | 0.0004 | 0.0010 |
| Spread | 0.0177 | 0.0165 | 0.0083 | 0.0142 | 0.0204 |
| Traded Value | 13.0518 | 0.1720 | 12.9355 | 13.0387 | 13.1901 |
| **Germany** | | | | | |
| Amihud | 0.0042 | 0.0041 | 0.0013 | 0.0028 | 0.0060 |
| Spread | 0.0136 | 0.0107 | 0.0068 | 0.0104 | 0.0168 |
| Traded Value | 12.1930 | 0.1390 | 12.1065 | 12.1709 | 12.2757 |
| **France** | | | | | |
| Amihud | 0.0117 | 0.0116 | 0.0034 | 0.0075 | 0.0177 |
| Spread | 0.0152 | 0.0113 | 0.0073 | 0.0127 | 0.0187 |
| Traded Value | 11.7888 | 0.1722 | 11.6797 | 11.7615 | 11.8779 |
| **Canada** | | | | | |
| Amihud | 0.0022 | 0.0023 | 0.0006 | 0.0014 | 0.0028 |
| Spread | 0.0125 | 0.0132 | 0.0041 | 0.0086 | 0.0155 |
| Traded Value | 12.5253 | 0.1437 | 12.4429 | 12.5117 | 12.6070 |
| **Japan** | | | | | |
| Amihud | 0.0379 | 0.0316 | 0.0131 | 0.0282 | 0.0579 |
| Spread | 0.0120 | 0.0095 | 0.0062 | 0.0083 | 0.0139 |
| Traded Value | 11.0635 | 0.7803 | 11.1265 | 11.1807 | 11.2911 |
| **China** | | | | | |
| Amihud | 0.0004 | 0.0004 | 0.0001 | 0.0003 | 0.0005 |
| Spread | 0.0093 | 0.0055 | 0.0054 | 0.0078 | 0.0113 |
| Trade Value | 12.7876 | 1.0939 | 12.9380 | 12.9891 | 13.1043 |
| **Australia** | | | | | |
| Amihud | 0.0021 | 0.0020 | 0.0008 | 0.0014 | 0.0028 |
| Spread | 0.0162 | 0.0143 | 0.0069 | 0.0115 | 0.0191 |
| Traded Value | 12.5392 | 0.1405 | 12.4510 | 12.5195 | 12.6219 |

On the other hand, we denote the wavelet coherency as,

$$R_{x,y}(f,\tau) = \frac{\left\|W_{x,y}(f,\tau)\right\|}{\left\|W_{x,x}(f,\tau^{1/2}W_{y,y}(f,\tau)^{1/2}\right\|},\tag{4}$$

where $<>$ represents a smoothing operator in both scale and time. Based on this definition, $R_{x,\ y}(f,\ \tau)$ is restricted by $0 \leqslant R_{x,\ y}(f,\ \tau) \leqslant 1.$.

Following, Liu (1994) we see that the benefits of wavelet coherency rests on its difference in time and, therefore its capacity to identify transitory relationships between the two time series. We compute the phase difference $\phi_{x,\ y}(f,\ \tau)$ as shown below.

$$\phi_{x,y}(f,\tau) = \tan^{-1}\frac{\Im\left(\langle W_{x,y}(f,\tau)\rangle\right)}{\mathscr{R}\left(\langle W_{x,y}(f,\tau)\rangle\right)}.\tag{5}$$

From the phase difference, we obtain the linkages existing between the two series both in phase and out of phase. We then use Monte Carlo approaches to test whether the wavelet patterns displayed by the wavelet approach is statistically significant.

## 4. Data, variable definition, summary statistics and time trends

We use daily data from 31st December 2019 until 10th July 2020 for G7 countries, China and Australia aggregate stock market indices to commute daily observations of 133 liquidity measures. The data for aggregate stock market indices of Canada (TSX 300 Composite Index), France (CAC 40 Index), Germany (DAX Composite Index), Italy (FTSE MIB Index), Japan (JPX-Nikkei Index 400), UK (FTSE All Share Index), USA (S&P 500 Index), Australia (S&P/ASX 200) and China (Shanghai SE Composite Index) are obtained from Thomson Reuters Eikon. The daily data on country specific COVID 19 infection cases and deaths are collected from Datastream.

Following the multidimensional nature of liquidity as expounded by Amihud (2002), in this paper we use three proxies to measure the stock market trading activities. Consistent with Corwin and Schultz (2012) we construct a high–low spread ratio (Spread) to capture the transaction cost aspect of liquidity. Consistent with Fernández-Amador, Gächter, Larch, and Peter (2013) we use traded value (Trade Value) to measure the trading activity. Following Amihud (2002), we measure illiquidity (ILLIQ) which we denote in the same way as Amihud to capture the price impact characteristics. From the market microstructure literature, among the three proxies, the Amihud (2002) measure is more prominent for its effectiveness over other high-frequency measures, and empirical support across different market structures (e.g., Acharya & Pedersen, 2005; Goyenko, Holden, & Trzcinka, 2009; Karolyi, Lee, & Van Dijk, 2012; Amihud, Hameed, Kang, & Zhang, 2015).

In Table 1, we report the descriptive statistics for our three liquidity proxies (Amihud, Spread and Traded Value). We observe that the USA shows the highest average daily illiquidity (0.070) followed by Japan (0.034) for the Amihud proxy. For the Spread proxy, we note that the UK shows the highest average (0.024) followed by Australia (0.016). In the case of Traded Value proxy, the highest mean was recorded by Italy (13.052) followed by the USA (13.028).

Table 2 presents the summary statistics of country level COVID 19 daily infections and deaths. As expected, we find that the highest average of COVID 19 cases (23,337) and standard deviation (29512) is associated with the USA, with the least average recorded cases (45) corresponding to Canada. On the average number of deaths recorded per country as a result of the COVID 19 outbreak, we again find that the highest mean (1014) and standard deviation (1515) is associated with the USA with the least mean deaths (1) linked to Australia. In Table 2.1 we present the ADF test of Dickey and Fuller (1979) and Phillips and Perron (1988) test to test for stationarity of our COVID-19 recorded cases and deaths. Results from the significant statistics show the proxies are stationary.

**Table 2**
Descriptive Statistics of COVID cases and deaths per country.

| Variable | Mean | Std Dev | Median |
|---|---|---|---|
| USA new cases | 23,337 | 29,512 | 18,279 |
| USA new deaths | 1014 | 1515 | 485 |
| UK new cases | 2212 | 4570 | 1059 |
| UK new deaths | 343 | 508 | 150 |
| Japan new cases | 92 | 129 | 41 |
| Japan new deaths | 5 | 11 | 1 |
| Italy new cases | 1,214 | 1,629 | 331 |
| Italy new deaths | 176 | 234 | 55 |
| Germany new cases | 985 | 1524 | 378 |
| Germany new deaths | 48 | 76 | 10 |
| France new cases | 868 | 1341 | 358 |
| France new deaths | 147 | 251 | 27 |
| Canada new cases | 552 | 625 | 313 |
| Canada new deaths | 45 | 61 | 9 |
| China new cases | 471 | 1545 | 29 |
| China new deaths | 27 | 116 | 0 |
| Australia new cases | 47 | 103 | 11 |
| Australia new deaths | 1 | 1 | 0 |

In Table 3, Panel A presents the ADF test of Dickey and Fuller (1979) and Phillips and Perron (1988) test to test for the stationarity of the examined liquidity variables. Results from the significant statistics show the proxies are stationary. Panel B of Table 3 reports the pairwise correlation between country specific liquidity proxies. We find significant positive correlation between the liquidity proxies, which are consistent with the theoretical arguments associated with the liquidity proxies used. We also observe some negative correlation between the liquidity measures. For the case of the USA, the UK, Canada, and Australia, we find significant positive correlation between all three liquidity proxies. For Italy and Germany, we note a significant negative correlation between Amihud and Traded Value. A negative correlation between Amihud and Traded Value could be attributable to the notion that stocks with high trading volume are more likely to be traded quickly as the adverse price impact caused by the order flow is lower (Dash et al, 2019).

Fig. 1 displays the time series plots of COVID 19 daily cases and liquidity proxies (Amihud, Spread, and Traded Value), while Fig. 2 illustrates time series plots of COVID 19 daily deaths and the three liquidity proxies. From the two plots, we observe strong co-movement between COVID 19 cases and deaths with the liquidity measures. We surmise then that an increase (decrease) in COVID 19 cases and deaths is associated with a decrease in stock market liquidity. A feature we investigate further below.

## 5. Empirical results discussion

### 5.1. Linear causality tests

Table 4 describes the linear Granger-causality test results between COVID-19 and the liquidity of G7 countries along with that of China and Australia. Panel-A of Table 4 reports linear causality between COVID-19 cases and stock market liquidity. Results reveal causality from COVID-19 daily infections rate to Amihud and Traded Value for the UK, Italy and France. Panel-B documents the causality between COVID-19 deaths and aggregate stock market liquidity. We observe that the number of deaths recorded greatly impacted market liquidity compared to the rate of infection. We make this conclusion because, we find causality from COVID-19 daily deaths recorded to Amihud and Traded Value for USA and France, Spread and Traded Value for the UK, Amihud and Spread for Canada, China and Germany. In the case of Italy, we observe causality from COVID-19 deaths recorded to all three liquidity proxies thus Amihud, Spread and Traded Value. For Australia, we find causality from COVID-19 deaths to the Amihud liquidity measure. The above results show that the number of deaths resulting from COVID-19 greatly affected the stock markets of countries which were greatly affected by the virus. For example, in the case of Italy, we note that both the number of infections and recorded deaths impacted market liquidity. For the USA stock market, we provide evidence that the number of deaths impacted trading activities compared to the number of infections as shown in Panel A. Comparing results reported in Panel A and Panel B, we find some country level differences in the COVID 19 pandemic and illiquidity relationship.

Recently, Baffes and Nagle (2020) find that the COVID-19 pandemic greatly affected the crude oil market with plummeting oil prices constituting the largest slump since the Gulf war. We attribute our documented evidence on the impact of COVID-19 on market liquidity to increased uncertainty in the economies of affected countries due to the COVID-19 outbreak. This is because prior literature shows that stock market performance can be negatively affected by a high level of uncertainty in the sense that uncertainty in economic policies cause market participants to embrace pessimistic considerations about expected discount rates, which may lead to a drop in share prices (Antonakakis, Chatziantoniou, & Filis, 2013; Pastor & Veronesi, 2012). Hence, countries in which the number of recorded deaths and infections such as the USA and Italy appears to be a strong predictor of stock return behavior, and if such countries exhibit significant illiquidity risk pricing, then following the liquidity shock hypothesis one may expect that the COVID-19 outbreak and (il) liquidity relationship in those markets to be more persuasive.

Overall, our results reveal a strong relationship between the COVID-19 outbreak and illiquidity measures for countries with high

**Table 2.1**

Unit-root test statistics (at level, with constant and trend) COVID cases and deaths per country.

| Variable | ADF | PP |
| --- | --- | --- |
| USA new cases | −10.574 | −6.093* |
| USA new deaths | −22.554*** | −16.503 |
| UK new cases | 9.140* | −7.410* |
| UK new deaths | −19.514* | −14.101 |
| Japan new cases | −22.089*** | −16.784 |
| Japan new deaths | −88.617* | −87.456* |
| Italy new cases | −3.861 | −2.887 |
| Italy new deaths | −3.929 | −2.888 |
| Germany new cases | −7.582 | −10.516 |
| Germany new deaths | −15.997 | −14.248 |
| France new cases | −15.955 | −29.407** |
| France new deaths | −24.832** | −17.339 |
| Canada new cases | −4.675 | −6.183 |
| Canada new deaths | −7.807 | −13.548 |
| China new cases | −47.067* | −66.142* |
| China new deaths | −119.598* | −129.317* |
| Australia new cases | −36.316* | −36.316** |
| Australia new deaths | −50.704* | −50.704* |

Notes: ***,** and * shows significance at 10%, 5% and 1% levels, respectively.

**Table 3**
Units root test and linear correlation.

| Panel A: Unit-root test statistics (at level, with constant and trend) | | | Panel B: Pairwise correlation between country level liquidity proxies | | |
|---|---|---|---|---|---|
| Countries | ADF | PP | Amihud | Spread | Traded Value |
| **USA** | | | | | |
| Amihud | −2.599** | −6.797* | 1 | | |
| Spread | −1.790* | −2.353* | 0.465* | 1 | |
| Traded Value | −1.340* | −1.652* | 0.390* | 0.813* | 1 |
| **UK** | | | | | |
| Amihud | −3.943* | −8.502* | 1 | | |
| Spread | −3.544* | −5.173* | 0.179 | 1 | |
| Traded Value | −2.955** | −3.087** | 0.091 | 0.582* | 1 |
| **Italy** | | | | | |
| Amihud | −5.431* | −9.205* | 1 | | |
| Spread | −5.765* | −6.389* | 0.080 | 1 | |
| Traded Value | −3.236* | −4.634* | −0.198*** | 0.512* | 1 |
| **Germany** | | | | | |
| Amihud | −3.574* | −8.732* | 1 | | |
| Spread | −2.012* | −3.728* | 0.294* | 1 | |
| Traded Value | −3.713* | −5.484* | −0.010* | 0.516* | 1 |
| **France** | | | | | |
| Amihud | −4.537* | −9.415* | 1 | | |
| Spread | −3.519* | −4.814* | 0.154 | 1 | |
| Traded Value | −3.624* | −4.810* | −0.108 | 0.627* | 1 |
| **Canada** | | | | | |
| Amihud | −3.159* | −4.875* | 1 | | |
| Spread | −0.977* | −2.371* | 0.466* | 1 | |
| Traded Value | −2.688* | −10.753* | 0.185*** | 0.501* | 1 |
| **Japan** | | | | | |
| Amihud | −5.014* | −9.223* | 1 | | |
| Spread | −2.544* | −4117* | 0.134 | 1 | |
| Traded Value | −0.613* | −0.655* | −0.125 | 0.193*** | 1 |
| **China** | | | | | |
| Amihud | −3.357* | −6.386* | 1 | | |
| Spread | −3.721* | −4.682* | 0.178* | 1 | |
| Trade Value | −0.660* | −0.647* | 0.102 | −0.017 | 1 |
| **Australia** | | | | | |
| Amihud | −4.443* | −10.076* | 1 | | |
| Spread | −4.799* | −4.779* | 0.442* | 1 | |
| Traded Value | −2.455* | −5.957* | 0.200*** | 0.529* | 1 |

Notes: ***,** and * shows significance at 10%, 5% and 1% levels, respectively.

infection rates and deaths. There could be three credible explanations for such a relationship. First, the increase in COVID-19 infections and deaths can distort market liquidity due to the lockdown that might have affected liquidity funding. Second, the causal link between COVID 19 outbreak and (il)liquidity may also be influenced by the stock market volatility and liquidity relationship. Third, as the outbreak of the virus increased uncertainty in affected economies (Sharif et al., 2020) and studies have shown that uncertainty accentuates the level of information asymmetry among investors (Nagar, Schoenfeld, & Wellman, 2019) an increase in information asymmetry may also adversely affect stock market (il)liquidity due to the increases in bid-ask spreads (Glosten & Harris, 1988).

## 5.2. Wavelet based time frequency domain analysis

To quantitatively assess the degree of causality interactions between the COVID-19 pandemic and stock market liquidity in different time scales we employ a continuous wavelet transform in order to track changes in phenomena over time. More precisely, a wavelet coherence technique was implemented to examine the short and long run effect of COVID-19 cases and deaths on aggregate
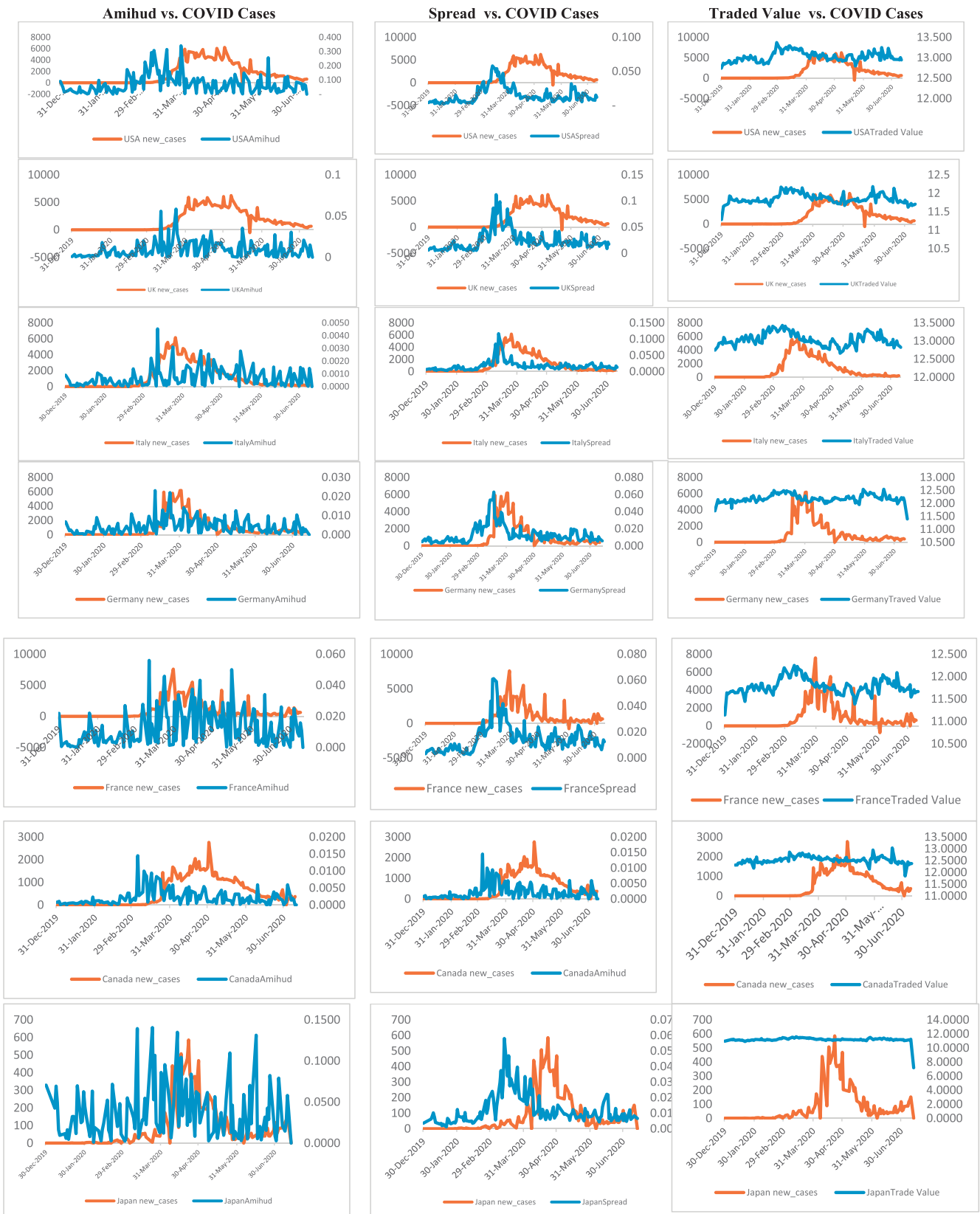
**Fig. 1.** Co-movements between COVID19 Cases and liquidity proxies per country.
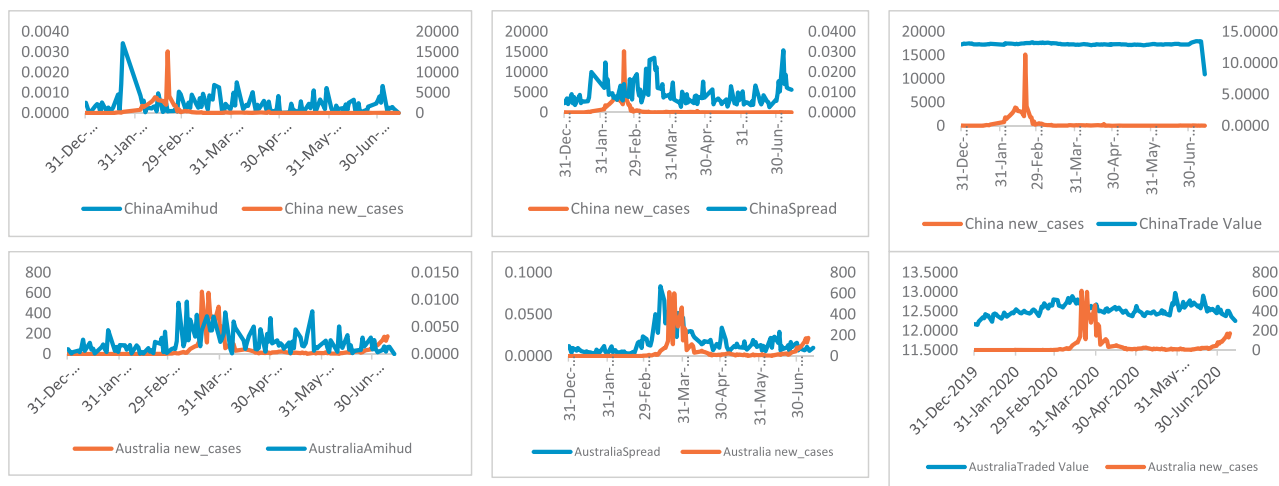
**Fig. 1.** (*continued*).

stock market liquidity of the G7 economies, China and Australia.

On wavelet coherency scalograms, the x- and y-axes refer to the time-scale space, in which the frequencies were shown as periods in days (the higher frequencies or lower scales are indicated at the top of the coherency map). In others, the x-axis indicates the time in terms of trading periods over the whole sample under study, while the y-axis represents the investment horizon, which refers to investors' holding periods (e.g. 1–2 days, 2–4 days, 4–8 days, etc.). The values of the wavelet coherency coefficients are represented with lower to higher strengths in blue to red colors. The degree of interdependence between the COVID-19 pandemic and stock market illiquidity indicators is given by the strength of the wavelet coherence of the COVID-19 outbreak- illiquidity pair indicating the spatial variability of the COVID-19 outbreak and its nexus with our three liquidity measures at different scales.

On the coherency scalograms the power of causality interplays is observed by the color code which varies from blue (low coherence relationship, the values of wavelet coherence coefficients are close to zero) to red (high coherence relationship, the values of wavelet coherence are close to one). The 5% statistical significance level for the coherency is displayed by thick contours on the coherence map, which is obtained from 1000 Monte Carlo Simulations. Inside the contour line we observe areas of strong coherence in time and period scales for the COVID-19 outbreak- illiquidity pair. The so-called cone of influence showing the region affected by edge effects is represented with a bold line. We neglect the areas outside the cone of influence as they do not hold significant confidence levels. Also, the application of this complex Morlet wavelet, as with the phase information (in-phase pattern, leading role, lagging role, or anti-phase pattern), enables the displaying of directionality in the dynamics between the COVID 19 outbreak- illiquidity pair for G7 countries, China and Australia.

In Fig. 3.1, we present wavelet coherency and phase differences between stock market liquidity proxies and COVID-19 reported cases and deaths for countries under examination. Figs. 3.1–3.9 plot the wavelet coherence between the stock market liquidity proxies and COVID-19 infected cases and deaths. For each country, the coherency between illiquidity and COVID-19 reported cases is displayed in the first column (a), while the relationship between illiquidity and COVID-19 reported deaths is illustrated in the second column (b).

Fig. 3.1a and 3.1b display the estimated wavelet coherences (WC, hereafter) and phase differences for USA aggregate stock illiquidity and COVID-19 infected cases and deaths respectively. In Fig. 3.1a, we detect the existence of small islands of strong dependence at the beginning, the mid and the end of the sample period over the 1–2 day frequency bands between all three liquidity measures (Amihud, Spread, Traded Value) and USA COVID-19 cases. We further observe strong dependency evidenced by large red islands at the middle of the sample period (29th February to 19th April) a period where the outbreak was at its peak globally over the 32–50 day frequency band for Amihud and Spread and USA COVID-19 infected cases. In the cases of Traded Value, the strength of the coherency declined over the 32–50 day frequency bands. This suggests that the USA market reacted to the bad news that emanated from China concerning the outbreak of the virus and the death of the first patient. The wavelet coherence between US stock market liquidity and COVID-19 reported deaths in Fig. 3.1b reveals huge islands of red color, which indicates strong dependency over the 1 to 8-day frequency bands for the whole sample period. Moreover, another high coherency area is identified in mid-February corresponding to some COVID-19 pandemic bad news such as the reported first patient death in the US on February 28th, the number of global cases raised to 87,000 and the high-level warning announced by the US authorities.

As for the connectedness between the UK aggregate stock market liquidity and COVID-19 infected cases (Fig. 3.2a), the WC depicts strong co-movement (deep red islands) at the beginning of the COVID-19 outbreak to the end of the entire sample period. It is worth mentioning that, at the very short run (1–4 day cycle), we observe a significant red-island for the entire period. In the long run (32–50 days) we find huge red islands around the peak of the outbreak (February to April) when the UK recorded a massive increase in the number of infected cases and the free fall of oil prices. Fig. 3.2b shows the wavelet plot between UK stock market liquidity and UK COVID-19 death counts. We identify an island of high dependence over the 16-day frequency band over the entire sample period. Other coherencies over 32–50 day frequency bands can be observed. In Italy where the coronavirus outbreak was very severe for both the number of infected cases and deaths reported, we find a very strong co-movement between stock market liquidity and COVID-19
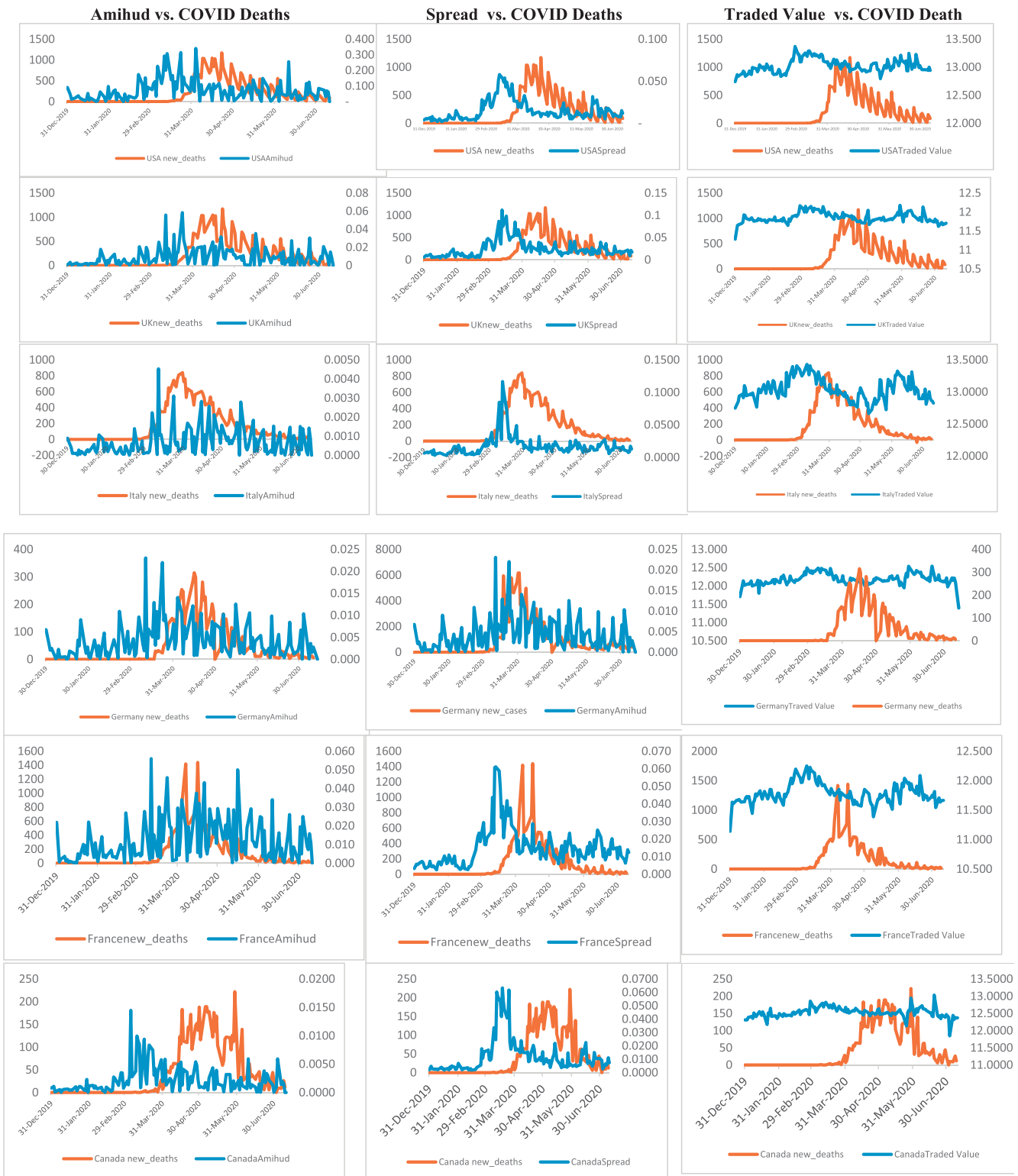
**Fig. 2.** Co-movements between COVID19 Deaths and liquidity proxies per country.

outbreak infected cases and deaths recorded for the entire period and the movement runs across frequency bands of 1–2,2–4,4–8,16–32 and 32–50 days. We find huge red islands for Spread liquidity measure and COVID-19 cases and deaths in Fig. 3.3a and 3.3b respectively. For the coherency between Germany market liquidity and COVID-19 infected cases (Fig. 3.4a) and COVID-19 death counts (Fig. 3.4b), even though we observed coherency in all cases as illustrated in Fig. 3.4, it is important to mention that, the WC reveals higher level of co-movement between Spread liquidity measure and COVID-19 infected cases over the entire sample period at all frequency bands.
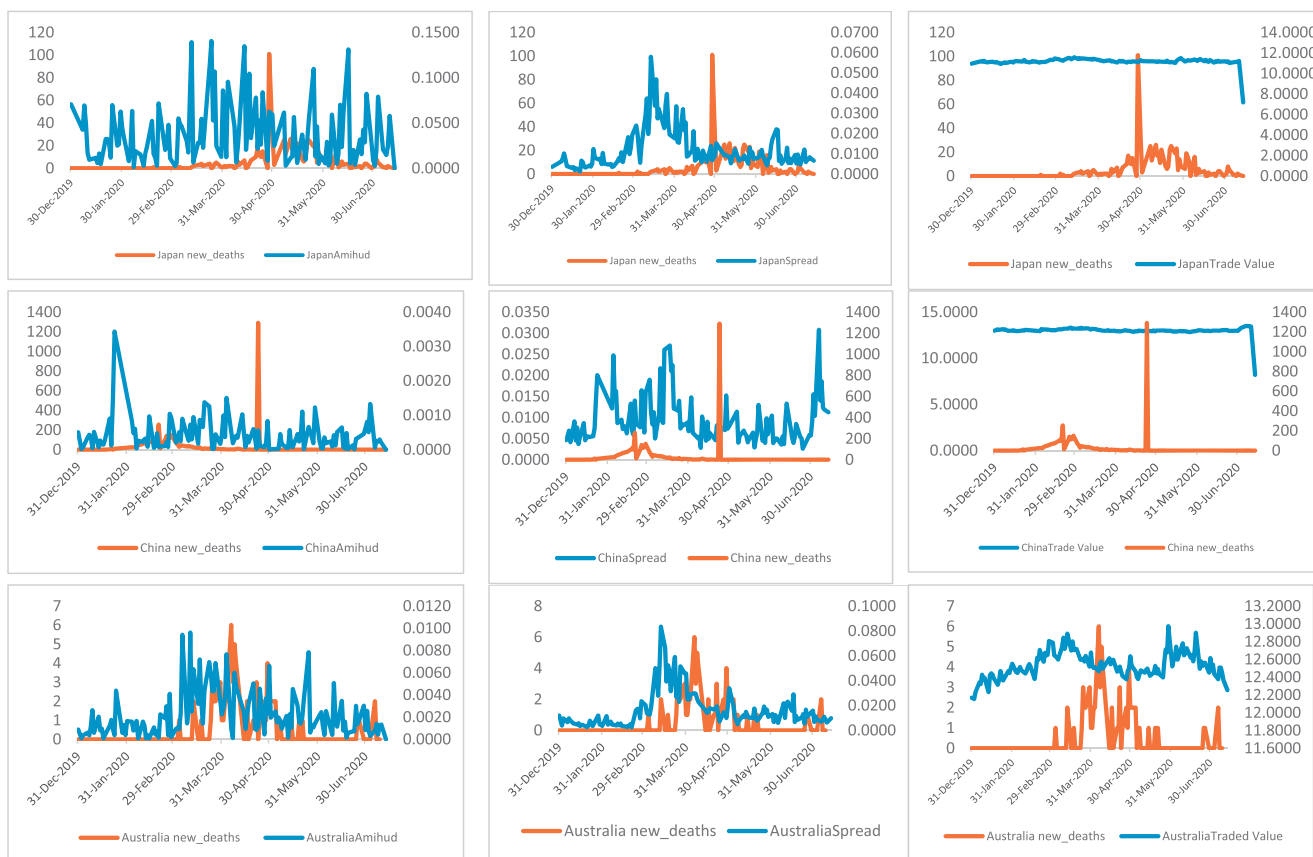
**Fig. 2.** (*continued*).

We identify a similar pattern with regards to islands of strong coherencies in Fig. 3.5 showing the coherence between the reported stock liquidity of France and COVID-19 infected counts (Fig. 3.5a) and COVID-19 deaths (Fig. 3.5b). For the strong co-movement between Spread and Traded Value and COVID-19 cases and deaths in France, we perceive that the COVID-19 outbreak has a greater effect on the French economic uncertainty. The red islands identified at the beginning and the end of the sample period correspond to lower frequencies (1 to 4 day frequency bands) which means that a long-term negative effect on the stock market was expected which is exactly what happened as the impact was very strong at the end of higher frequencies.

Fig. 3.6 plots the wavelet coherence between Canada stock market liquidity and US COVID-19 infected cases (Fig. 3.6a) and death (Fig. 3.6b), while Fig. 3.7 displays the connectedness between Japan stock illiquidity and COVID-19 reported cases (Fig. 3.7a) and deaths (Fig. 3.7b). Similar to the above findings, it also documents strong coherency between illiquidity and COVID-19 outbreaks, for both Canada and Japan where the number of recorded cases and deaths were high at the beginning of the outbreak, we identity strong red islands at lower frequency bands (1–2, 2–4, 4–8) days for the entire period. However, at the 32–50 frequency bands, we find minimal level of co-movement between illiquidity and COVID-19 pandemic for both Canada and Japan.

Besides focusing on the G7 countries, we further test the coherency between stock market liquidity and COVID-19 outbreaks for China where the virus began and Australia given that Australia recorded minimal cases and deaths as result of COVID-19 for the sample period. For China, we find from Fig. 3.8 that the effects of COVID-19 outbreak on liquidity was strong at lower frequencies of 1–2 and 2–4 days for all liquidity measures. In Fig. 3.9 we find, for the case of Australia, strong connections between Amihud and Spread liquidity proxies and COVID-19 infected cases and deaths for the entire period. The effects were stronger during the peak of the outbreak at frequency bands 1–2 and 2–4.

Next, we focus on the phase difference displayed beneath Figs. 3.1–3.9 which are also very informative. Accordingly, to study the lead-lag nexus between aggregate market liquidity and COVID-19 infected cases and death counts in G7 countries, China and Australia, we refer to the phase-differences. It is important to note that the phase diagrams for all studied pairs present a quite similar pattern with values of phase-differences ranging between $-\pi/2$ and $\pi/2$ at all frequency bands and for the entire period under study, indicating that aggregate market liquidity of countries and COVID-19 outbreak were constantly in-phase at any point in time. With reference to the phase diagrams, it is remarkable that transport for most countries COVID-19 reported cases and death counts were leading for long holding period such as 8–32 days and 32–50 days.

To briefly sum up, our findings show that the COVID-19 outbreak had a strong bearing on illiquidity globally. It is not surprising major markets around the world performed poorly during the peak of the outbreak because of increased uncertainty. For example, Baker et al. (2020) observe that the COVID-19 pandemic has had a worse impact on stock markets than any other infectious disease such as Spanish Flu. Overall, our results reveal a strong co-movement between COVID-19 and the country-specific (il)liquidity

**Table 4**
Linear causality: COVID 19 Pandemic and (il)liquidity.

Panel A: Linear causality: COVID 19 Cases and (il)liquidity

| Countries | H0: COVID 19 Cases does not cause (il)liquidity | | | H0: (il)liquidity Cases does not cause COVID 19 Cases | | |
|---|---|---|---|---|---|---|
| | Amihud | Spread | Traded Value | Amihud | Spread | Traded Value |
| USA | 0.365 | 0.622 | 0.510 | 4.794 | 4.477 | 0.992 |
| | [0.545] | [0.430] | [0.475] | **[0.029]** | **[0.034]** | [0.319] |
| UK | 2.980 | 0.079 | 3.685 | 0.013 | 1.512 | 0.102 |
| | **[0.084]** | [0.778] | **[0.055]** | [0.909] | [0.214] | [0.749] |
| Italy | 5.695 | 0.035 | 11.416 | 0.165 | 0.582 | 0.343 |
| | **[0.017]** | [0.853] | **[0.001]** | [0.685] | [0.446] | [0.558] |
| Germany | 1.004 | 0.039 | 1.436 | 1.979 | 4.371 | 0.167 |
| | [0.316] | [0.844] | [0.231] | [0.159] | **[0.037]** | [0.683] |
| France | 7.908 | 1.387 | 7.995 | 1.449 | 8.506 | 0.154 |
| | **[0.005]** | [0.239] | **[0.005]** | [0.229] | [0.004] | [0.695] |
| Canada | 0.308 | 1.033 | 0.550 | 4.682 | 4.381 | 0.007 |
| | [0.578] | [0.309] | [0.458] | **[0.030]** | **[0.036]** | [0.993] |
| Japan | 0.022 | 0.758 | 0.205 | 0.871 | 4.163 | 0.014 |
| | [0.882] | [0.384] | [0.651] | [0.35] | [0.041] | [0.905] |
| China | 1.956 | 2.165 | 0.427 | 0.451 | 0.306 | 0.041 |
| | [0.162] | [0.141] | [0.513] | [0.502] | [0.580] | [0.834] |
| Australia | 1.426 | 0.233 | 0.598 | 3.384 | 2.433 | 0.005 |
| | [0.232] | [0.629] | [0.439] | **[0.066]** | [0.119] | [0.942] |

**Panel B: Linear causality: COVID 19 Deaths and (il)liquidity**

| Countries | H0: COVID 19 Death does not cause (il)liquidity | | | H0: (il)liquidity does not cause COVID 19 Death | | |
|---|---|---|---|---|---|---|
| USA | **0.085** | 0.173 | **2.536** | 0.586 | 1.026 | 0.002 |
| | **[0.077]** | [0.678] | **[0.011]** | [0.444] | [0.311] | [0.963] |
| UK | 0.563 | **2.811** | **8.128** | 1.815 | 2.796 | 0.244 |
| | [0.453] | **[0.094]** | **[0.004]** | [0.174] | [0.094] | [0.621] |
| Italy | **6.834** | 1.377 | **5.107** | 0.294 | 0.176 | 0.031 |
| | **[0.009]** | [0.675] | **[0.025]** | [0.588] | [0.675] | [0.860] |
| Germany | **1.971** | **3.432** | 1.599 | 1.769 | 2.180 | 0.004 |
| | **[0.010]** | **[0.064]** | [0.206] | [0.184] | [0.140] | [0.984] |
| France | **6.568** | 1.367 | **2.969** | 1.274 | 2.657 | 0.357 |
| | **[0.010]** | [0.242] | **[0.085]** | [0.721] | [0.103] | [0.550] |
| Canada | **0.029** | **0.822** | 0.010 | 0.627 | 0.652 | 2.306 |
| | **[0.0863]** | **[0.065]** | [0.919] | [0.428] | [0.420] | [0.129] |
| Japan | 2.341 | 0.729 | 0.037 | 0.026 | 0.493 | 0.006 |
| | [0.126] | [0.395] | [0.847] | [0.870] | [0.516] | [0.938] |
| China | **1.105** | **3.990** | 0.765 | 0.103 | 0.422 | 0.002 |
| | **[0.029]** | **[0.046]** | [0.382] | [0.748] | [0.516] | [0.969] |
| Australia | **3.128** | 0.799 | 0.140 | 4.656 | 4.445 | 0.133 |
| | **[0.077]** | [0.371] | [0.707] | [0.031] | [0.035] | [0.715] |

Note: This table reports Chi square-Statistics of linear causality tests between COVID 19 pandemic and liquidity. Figures in curly brackets are p-values. p < 0.10, < 0.05 and < 0.01 shows significance at 10%, 5% and 1% levels, respectively.

measures of Italy, Germany, France, the USA and the UK. The co-movements are found in all frequency bands between 1 and 2 days, 2–4 days, 8–32 days and 32–50 days, which suggest that the effects of COVID-19 cases and deaths create uncertainty that last longer (up to 50 days) in the developed markets. The findings of Ko and Lee (2015) also corroborate our results that high uncertainty has strong effects for stock markets in, Germany, the United Kingdom, and the United States.

To explain our results, we argue that the variation of frequency bands across countries induced by the outbreak of COVID-19 may also be related to their market structure, market participants' behavior, and level of market integration with other markets. The geographic, economic, and political environment could also affect the importance of liquidity risk differently across countries (Lee, 2011). We make this claim because, the spread of COVID-19 related information may facilitate the pricing of negative news about future performance of the economy in the stock market. This, in turn, may induce a widespread portfolio repositioning. Also, investors may be prone to rebalancing their portfolios towards safer assets. All these may result in additional trading, which affect equity market liquidity. Additionally, the results on the effects of COVID-19 recorded cases and deaths on stock liquidity are in line with our expectations. This is because, the number of COVID-19 cases and deaths led to the closure of financial institutions which posed a challenge to market participants' trading possibilities, thus damaging stock market liquidity. Other phenomena that may explain the impact of COVID-19 on stock market liquidity, may be irrational behaviors that are likely to be more pronounced in emerging markets.
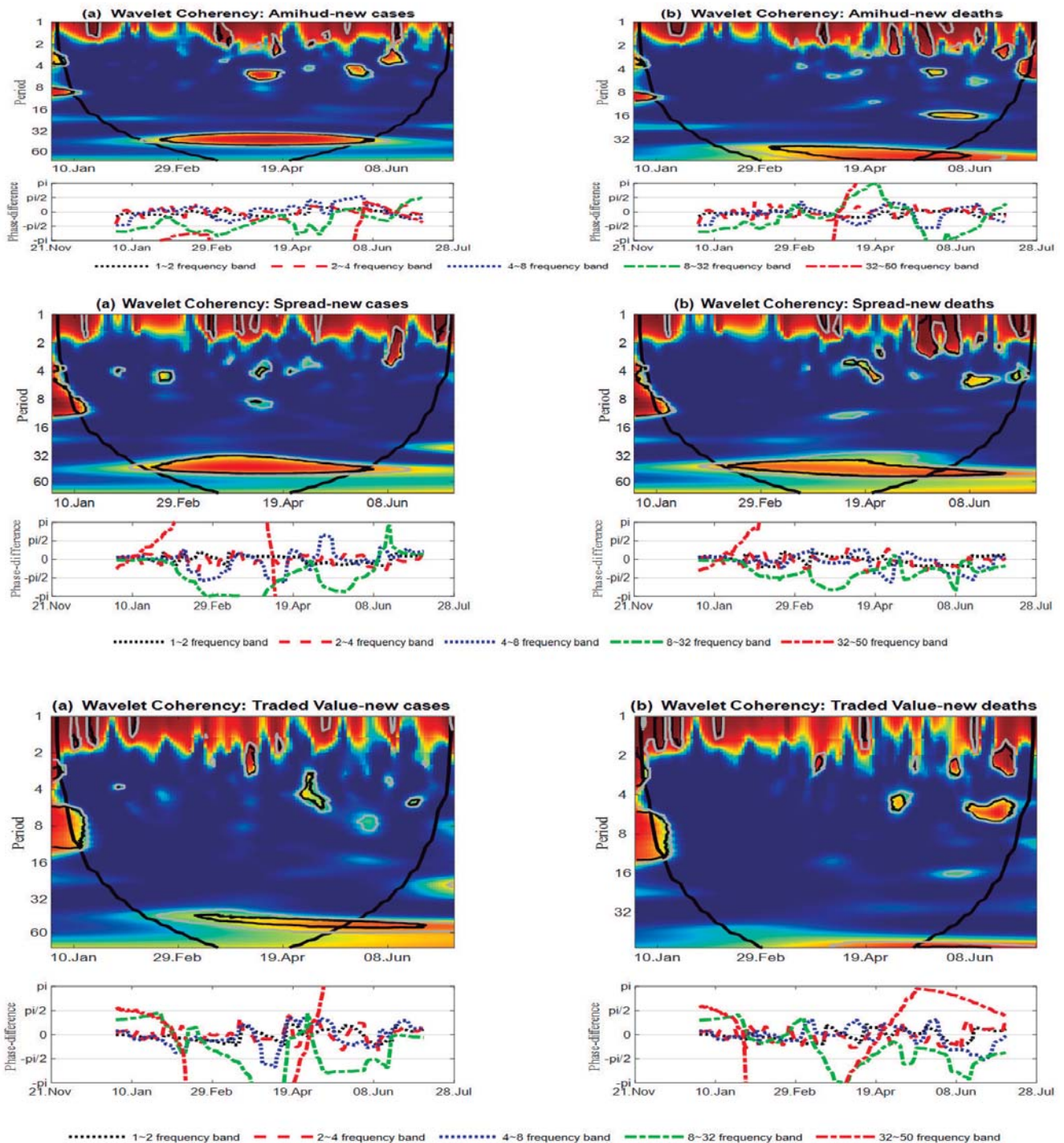
**Fig. 3.1.** USA Wavelet coherence between COVID 19 and (il) liquidity.

These include the tendency to ignore bad news, demonstrated by the "ostrich effect" (Galai & Sade, 2006), the "information overload" effect (Agnew & Szykman, 2005), the negative effect of bad experience (Thaler & Johnson, 1990), and the disposition effect (Shefrin and Statman, 1985), which refers to the reluctance of investors to incur losses and to hold loser stocks for too long. All these potential behavioral drivers may lead to lower levels of market liquidity. Related literature suggests that commonality in liquidity varies across countries and over time (Karolyi et al., 2012), and the commonality in illiquidity return premium is stronger in markets that are financially integrated with other markets (Amihud et al., 2015). Another possible explanation for the variation of frequency bands across countries could be due to the difference in market participants' behavior. The viability of profitable trading strategies for short- and long-term investors (or the retail and institutional investors) in different countries could be different given the implication of transaction cost variation for these two types of investors. A short-horizon calls for investing in liquid assets, whereas a long investment horizon enables the investor to earn higher net return (after transaction cost) by investing in illiquid assets (Amihud & Mendelson, 1991). While the short-term investor is more interested in short-run (higher frequency) market movements, the latter is more
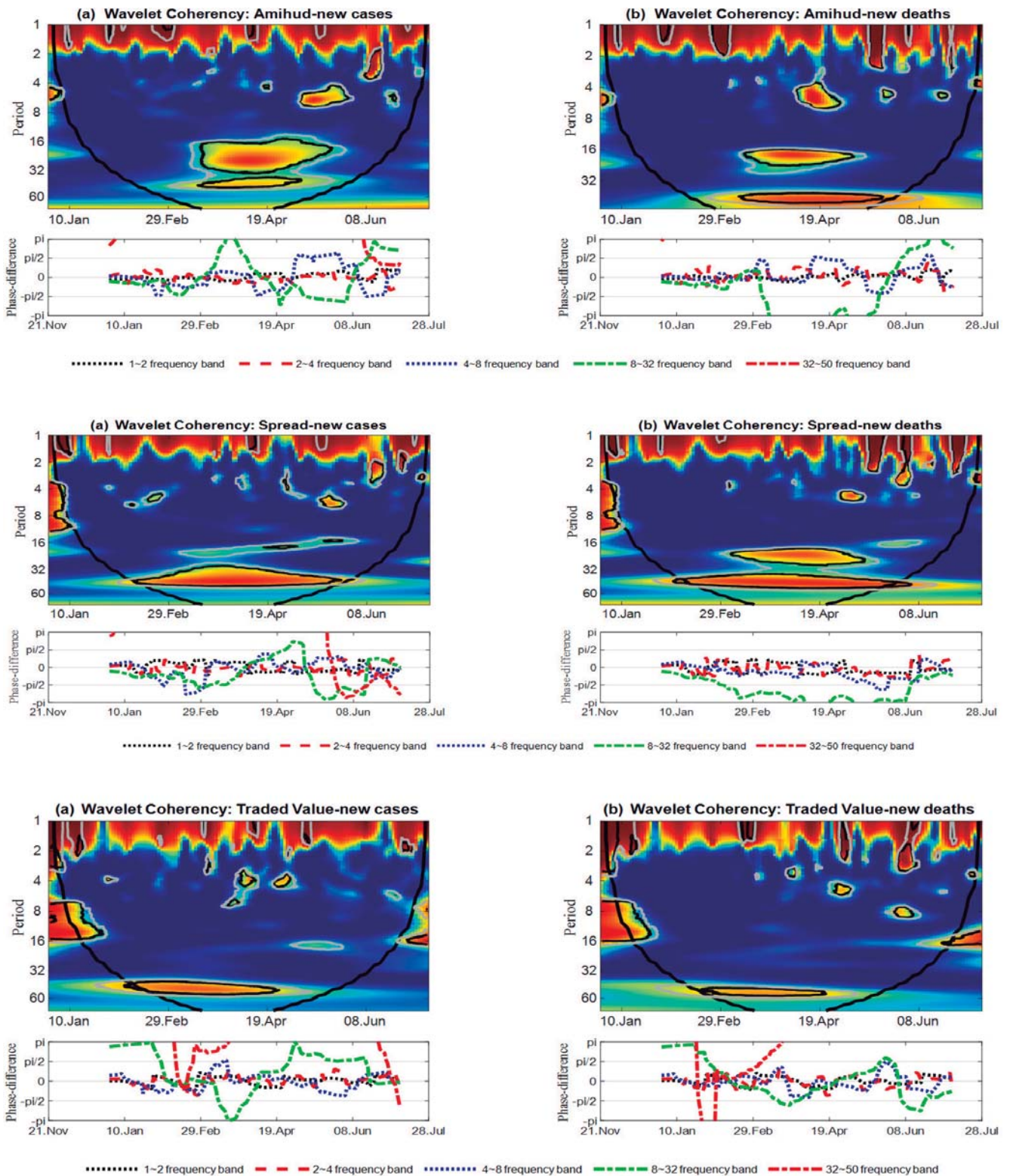
**Fig. 3.2.** UK Wavelet coherence between COVID 19 and (il) liquidity.

concerned with long-run (lower frequency) market movements. That is if the degree of the co-movement between COVID-19 and (il) liquidity varies across frequencies the investment risk management for each type of investor will also be different. Wavelet analysis aids to assess the strength of the co-movement (in this case COVID-19 outbreak and liquidity) simultaneously at different frequencies, and how such strength has evolved over time. To a certain extent, the observed pattern of variation in frequency bands across countries could also be due to the different types of investor participation in different countries.
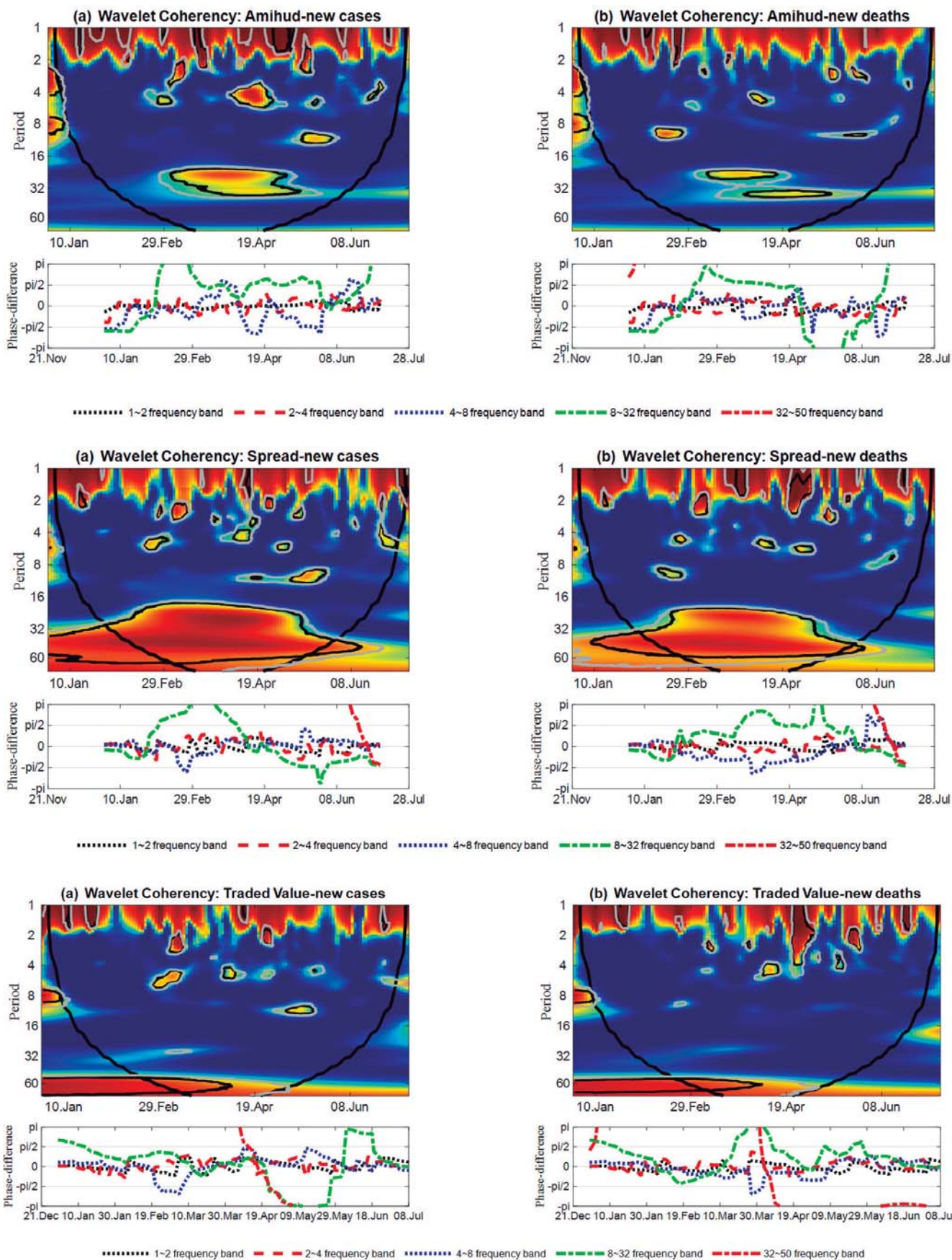
**Fig. 3.3.** Italy Wavelet coherence between COVID 19 and (il) liquidity.
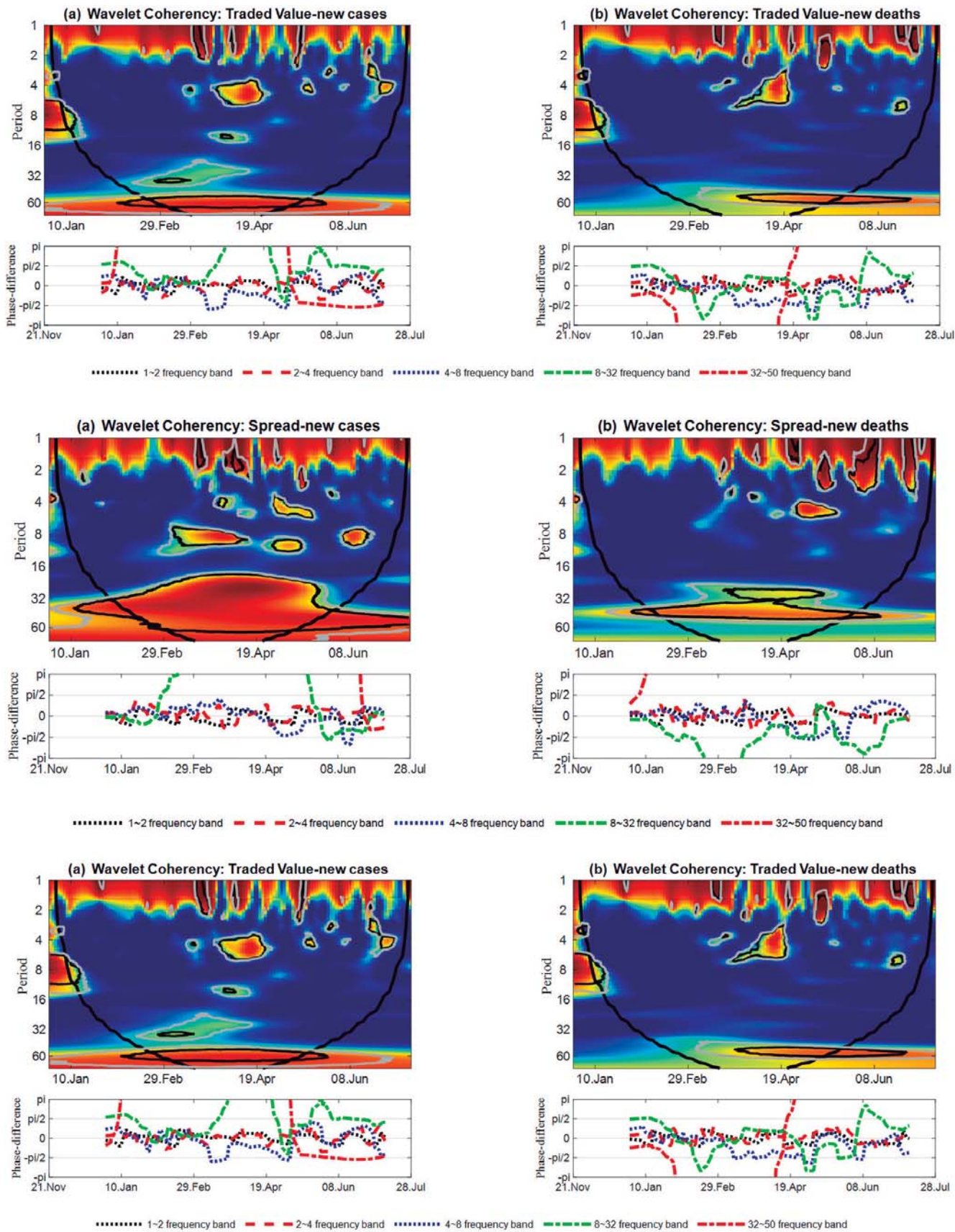
**Fig. 3.4.** Germany Wavelet coherence between COVID 19 and (il) liquidity.
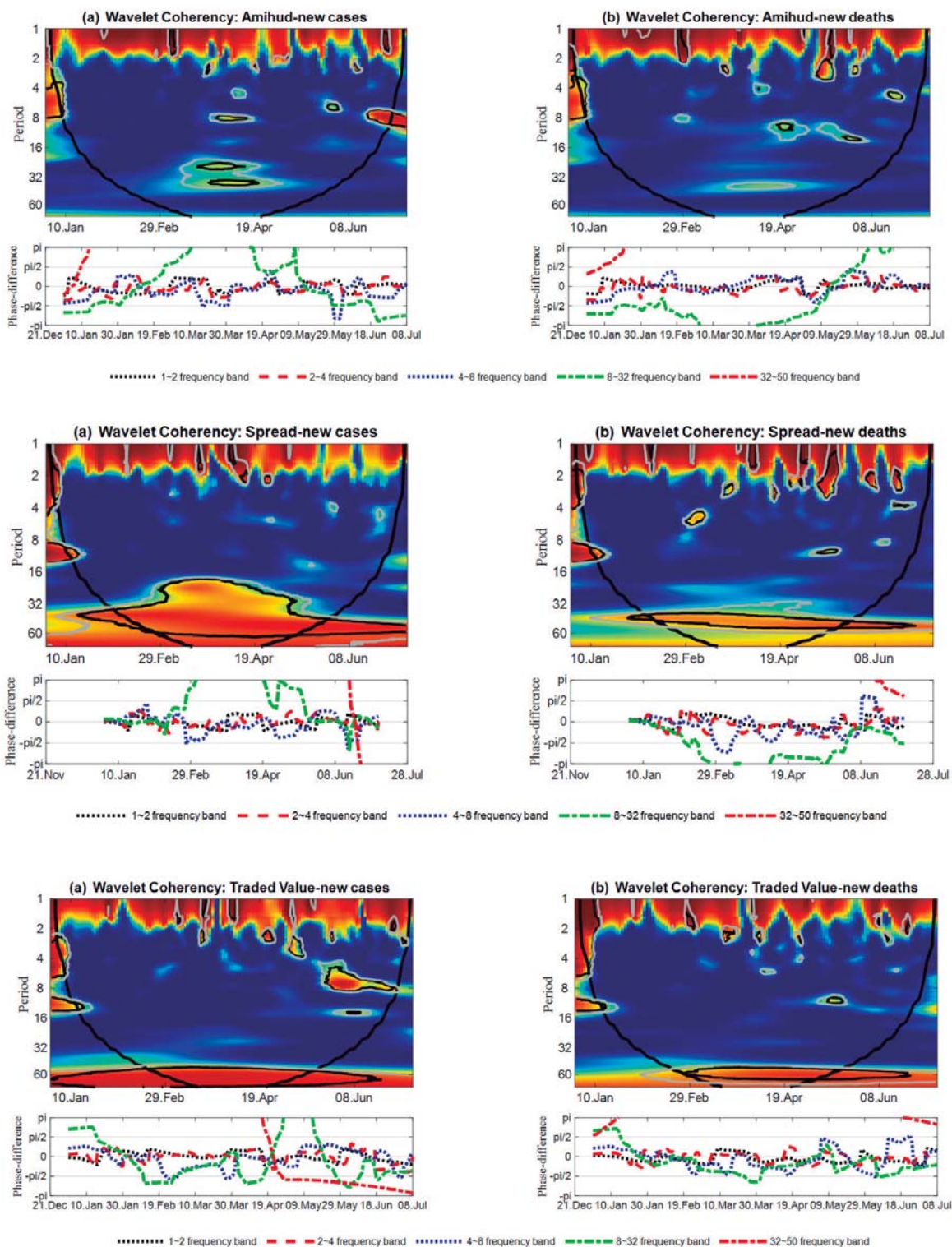
**Fig. 3.5.** France Wavelet coherence between COVID 19 and (il) liquidity.

## 6. Conclusions

This paper investigates stock market liquidity and COVID-19 co-movement within the G7 countries, China and Australia using country level aggregate stock market liquidity and COVID-19 infected cases and deaths. To study the synchronization between illiquidity and the COVID-19 outbreak across the selected countries at different periods, we employ wavelet coherency based on a continuous wavelet transforms. Results from the wavelet coherency indicate that co-movements of market liquidity and COVID-19 outbreak are multi-scale in nature. Specifically, our analysis documents that illiquidity and COVID-19 cases and deaths co-move strongly at low frequencies.
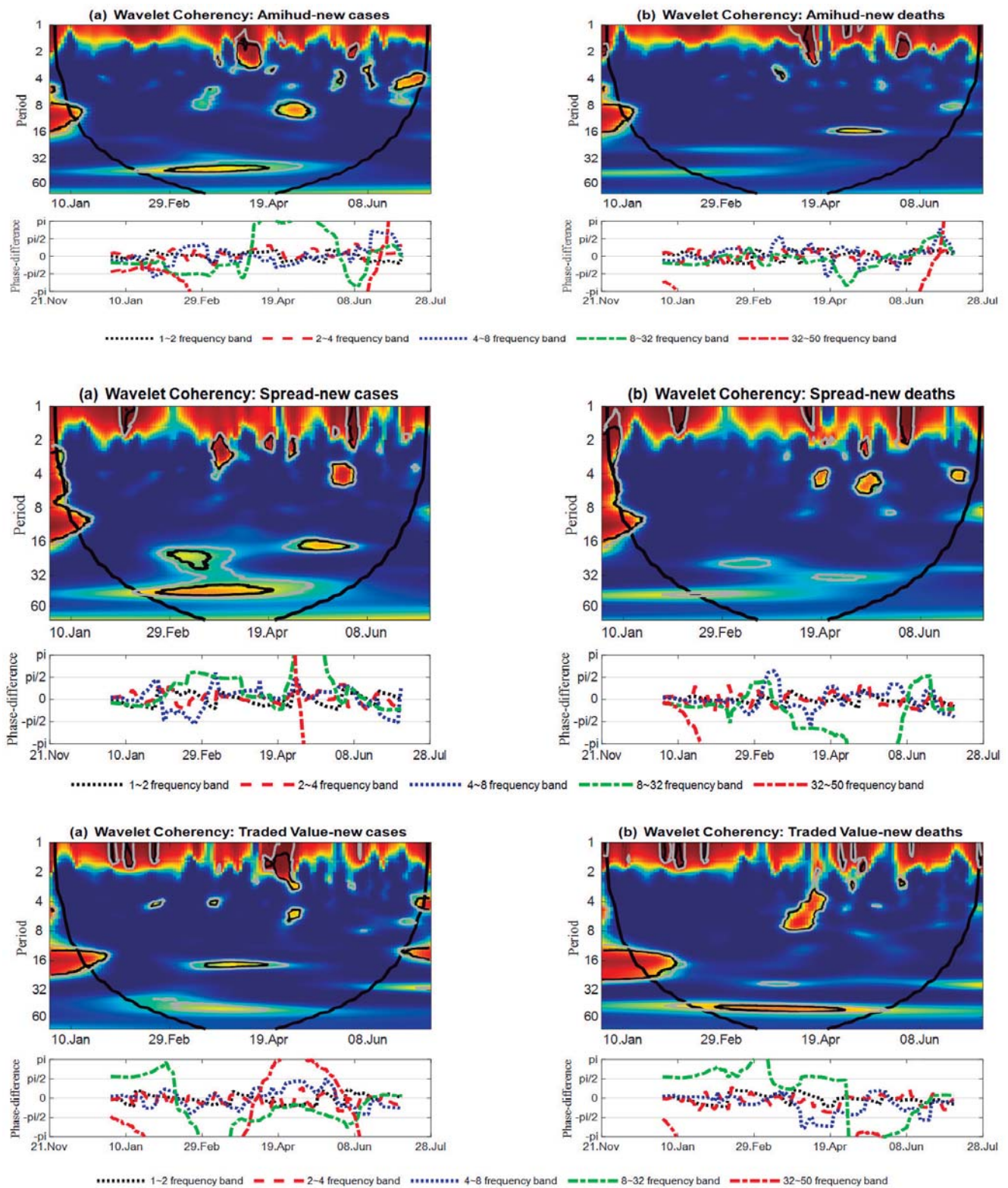
**Fig. 3.6.** Canada Wavelet coherence between COVID 19 and (il) liquidity.

Our results suggest that portfolio managers and treasury departments of financial institutions should care more about market (il) liquidity for the time or investment horizon in the short and long run. Consistent with Amihud and Mendelson (1991) observation, one might recommend that public authorities should avoid laws and regulations that hurt the liquidity of capital markets. The results also suggest that when market liquidity suffers and leads to uncertainty in the economic environment, policymakers can intervene with prompt corrective actions such as increasing bond purchase to inject liquidity (Iwatsubo & Taishi, 2018), and facilitate liquidity adjustment by offering competitive rates in comparison to short-term money market rates. The results can be also valuable for portfolio
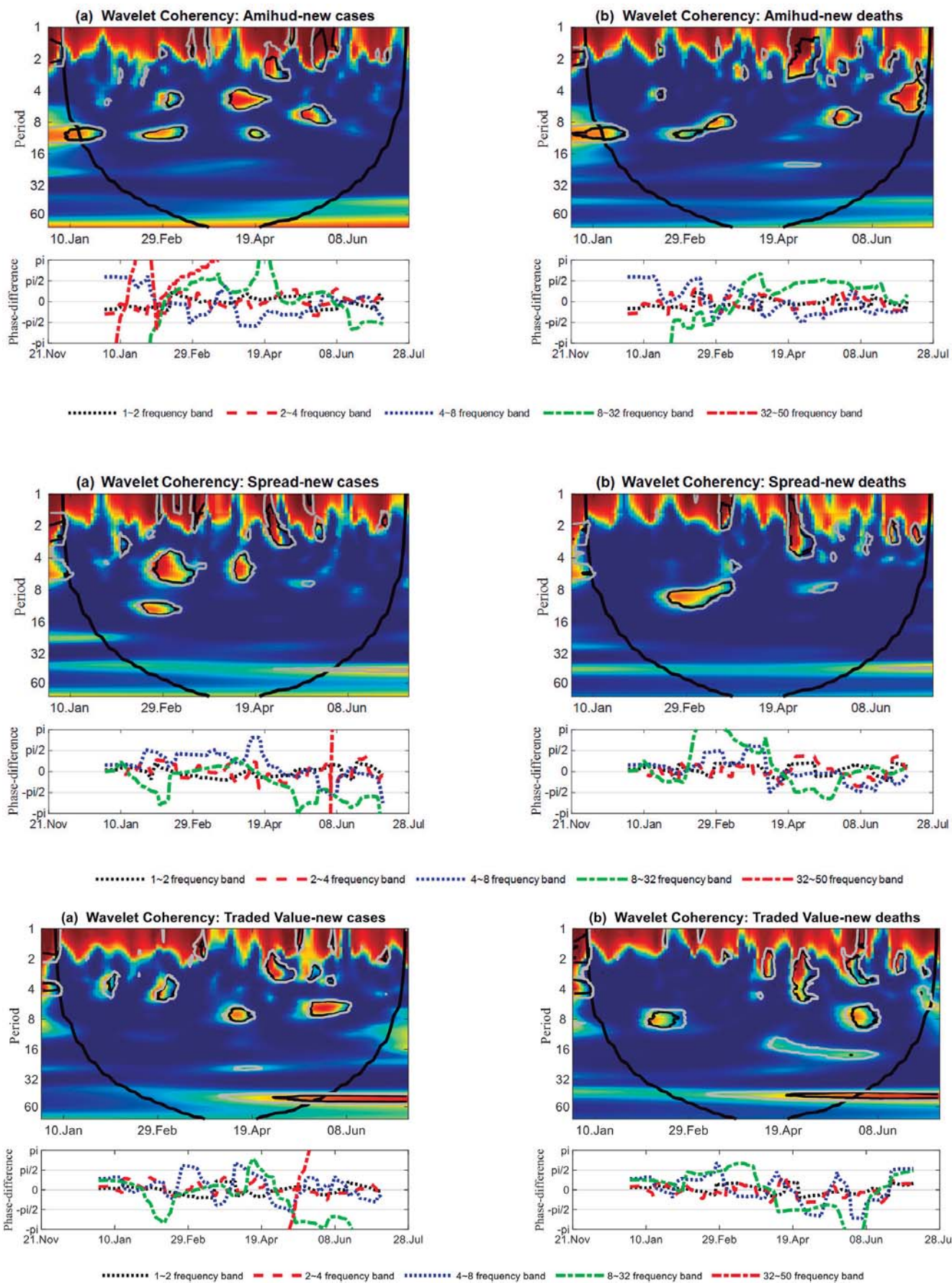
**Fig. 3.7.** Japan Wavelet coherence between COVID 19 and (il) liquidity.
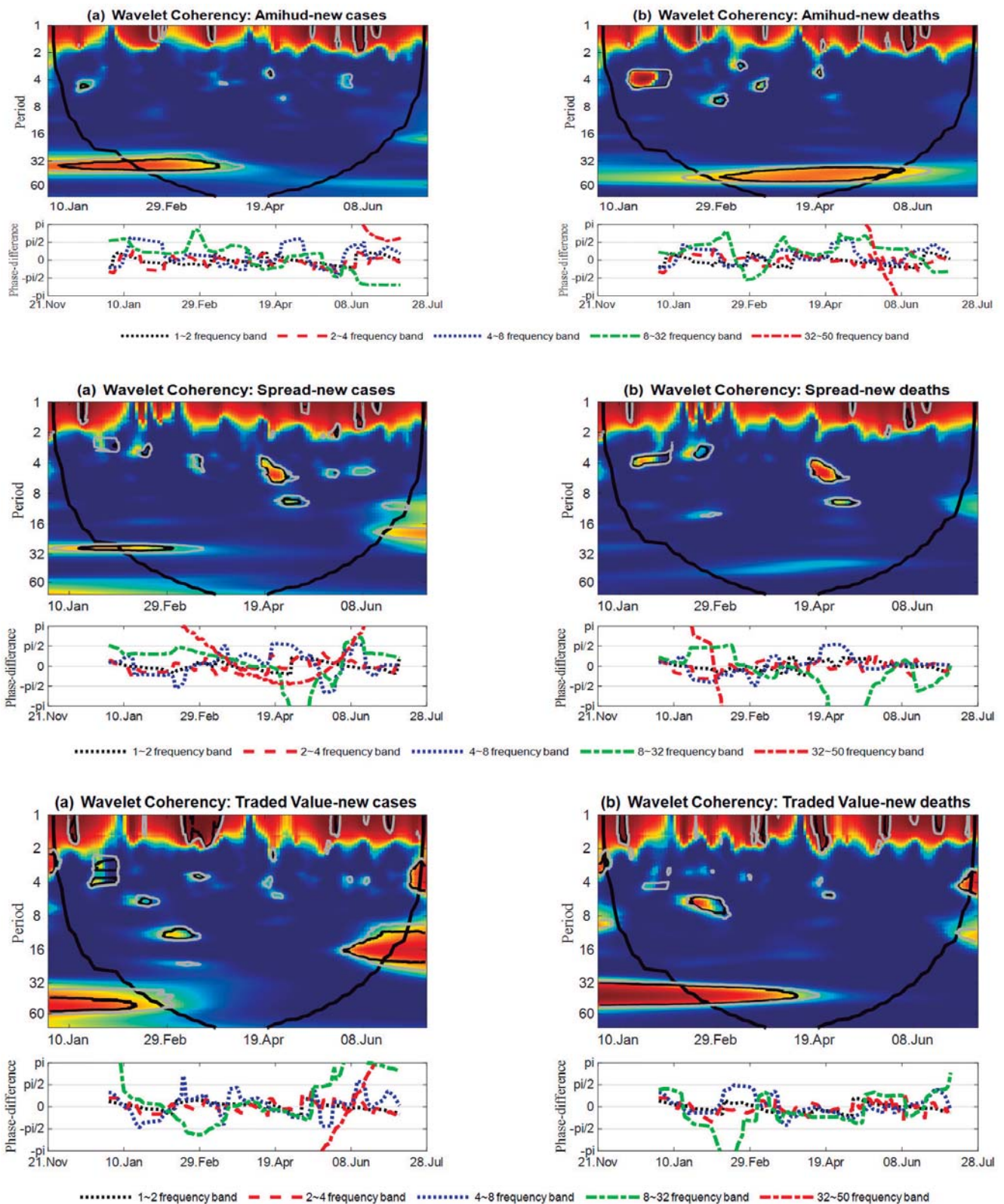
**Fig. 3.8.** China Wavelet coherence between COVID 19 and (il) liquidity.

managers in forecasting market risk. Our results may help investors to consider the dynamics of the stock markets in the short run in order to learn how to invest in comparable conditions in the future. Additionally, our findings have significant implications for policymakers. Effective partnerships in relation to policy between governments and central banks in addition to securities regulators may help them to deal with this pandemic challenge. This could make investors more optimistic about firms' future earnings, which, in turn, might lessen market instabilities. Further, regulatory authorities should plan proactive workshops to increase the confidence of
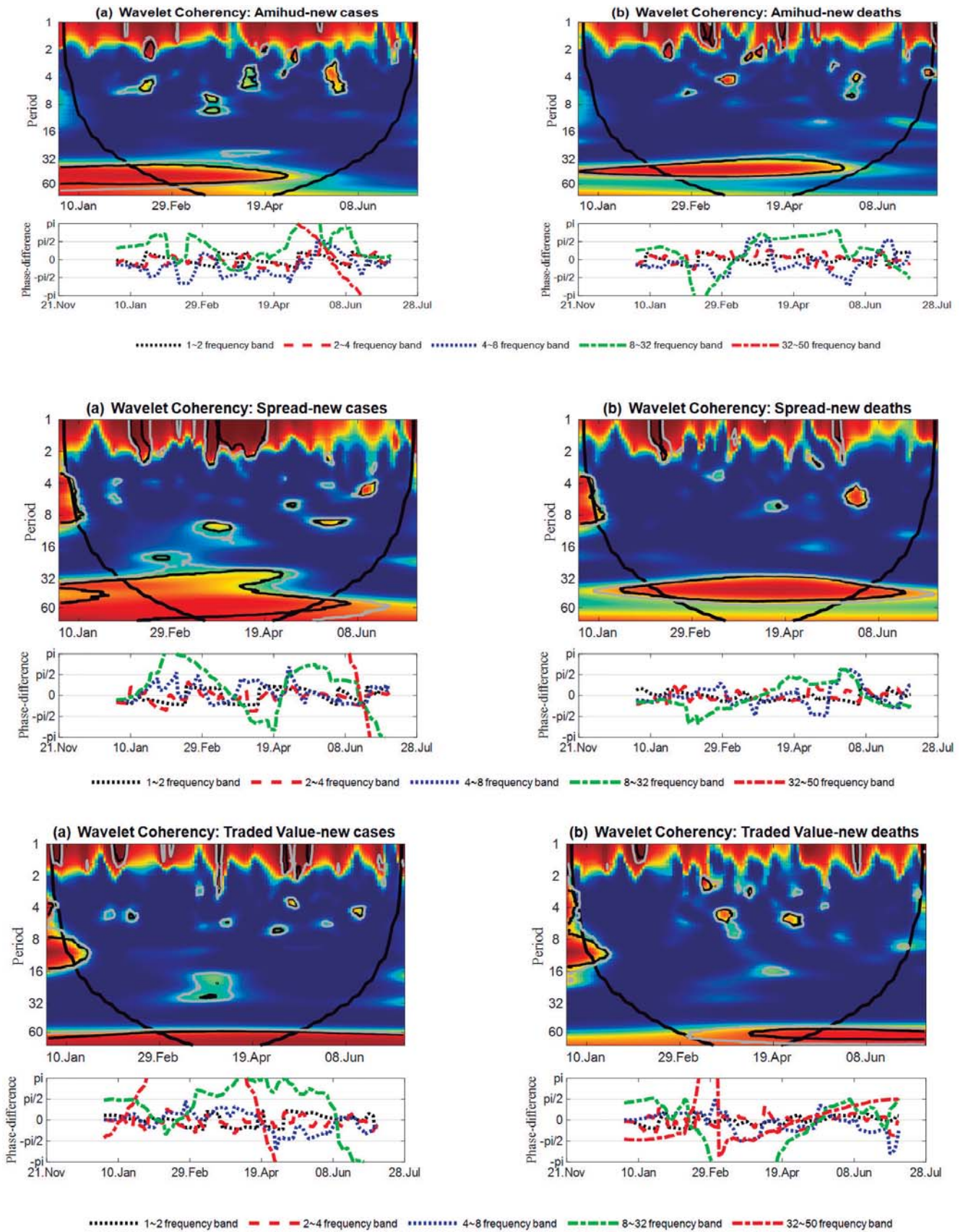
**Fig. 3.9.** Australia Wavelet coherence between COVID 19 and (il) liquidity.

investors after malign events such as COVID-19. Given that this is now an emerging area of research, we recommend that future studies examine whether the market microstructure differs across different asset classes, e.g. indices vs individual stocks; growth indices vs value indices (stocks) etc. using robust estimation techniques.

## Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

## Data availability

Data will be made available on request.

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