Heliyon 7 (2021) e06181

Contents lists available at ScienceDirect

Heliyon

journal homepage: www.cell.com/heliyon

Research article

Unconditional and conditional analysis between covid-19 cases, temperature, exchange rate and stock markets using wavelet coherence and wavelet partial coherence approaches

Gagan Deep Sharma [a], Aviral Kumar Tiwari [b,c,*], Mansi Jain [a], Anshita Yadav [a], Burak Erkut [d,e]

[a] University School of Management Studies, Guru Gobind Singh Indraprastha University, Sector 16 C, Dwarka, New Delhi, India
[b] Department of Finance and Economics, Rajagiri Business School, Rajagiri, Valley Campus, Kochi, India
[c] South Ural State University, Lenin Prospect 76, Chelyabinsk, 454080, Russian Federation
[d] Faculty of Economics, Administrative and Social Sciences, Bahçeşehir Cyprus University, Nicosia, Cyprus
[e] Institute for Research in Economic and Fiscal Issues, Paris, France

ARTICLE INFO

Keywords:
COVID-19
Wavelet coherence
Partial wavelet coherence
Temperature
Stock market return
Exchange rate return

ABSTRACT

This paper examines the time-frequency relationship between the number of confirmed COVID-19 cases, temperature, exchange rates and stock market return in the top-15 most affected countries by the COVID-19 pandemic. We employ Wavelet Coherence and Partial Wavelet Coherence on the daily data from 1st February, 2020 to 13th May, 2020. This study adds to the literature by implementing the Wavelet Coherence technique to explore the unexpected outbreak effects of the global pandemic on temperature, exchange rates and stock market returns. Our results reveal (i) there is evidence of cyclicality between temperature and COVID-19 cases, implying that average daily temperature has a significant impact on the spread of the COVID-19 disease in most of the countries; (ii) strong connectedness at low frequencies display that COVID-19 cases have a significant long-term impact on the exchange rate returns and stock markets returns of the most affected countries under study; (iii) after controlling for the effect of stock market returns and temperature, the co-movements between the confirmed COVID-19 cases and exchange rate returns becomes stronger; (iv) after controlling for the effect of exchange rate returns and temperature, the co-movements between the confirmed COVID-19 cases and stock market returns become stronger. Apart from theoretical contribution, this paper offers value to investors and policymakers as they attempt to combat the coronavirus risk and shape the economy and stock market behavior.

1. Introduction

Within four months of the World Health Organization confirming the novel nature of the SARS-CoV-2 (popularly known as the Coronavirus disease or COVID-19) (on 9th January 2020), and two months of the disease being declared as a global pandemic (11th March 2020), the number of cases and deaths across the world have crossed 4.5 million and 0.3 million respectively, as on 17th May 2020 (Github, 2020). The severity of the crisis is mainly driven by its highly contagious nature ($R^0 = 2$–5), which implies that one patient can infect two to five people. The symptoms of COVID-19 include cold, fever, dry cough, myalgia, fatigue, pneumonia, anorexia, diarrhea, arrhythmia, and septic shock, etc., which are mostly flu-like symptoms, primarily caused by weather- and environment-related factors (Wang et al., 2020b). Investigating the relationship of COVID-19 cases with the weather makes a strong case. Several recent studies (Huang et al., 2020; Park et al., 2020; Wang et al., 2020a; Yao et al., 2020) have taken the daily average temperature as the key variable representing weather.

Based on the climatic determinants analysis, there is evidence that temperature affects the transmission of influenza epidemics (Bedford et al., 2015; Tamerius et al., 2011). Previous experience with the SARS reported that the disease disappeared in warm weather (Wallis and Nerlich, 2005). Some experts expect the same behavior in case of COVID-19, as it falls into the same family of corona-virus (Wilder-Smith et al., 2020). Extant literature highlights the temperature may still have a moderate impact on spread of the COVID-19 virus (Liu et al., 2020b; Qi et al., 2020; Shi et al., 2020; Xie and Zhu, 2020). A report online concludes that with low temperature and dry air in the wintertime shall precipitate the spread of coronavirus in the later part of the year (Molteni, 2020). Another report by the Week (2020) highlights COVID-19

* Corresponding author.
E-mail address: aviral.eco@gmail.com (A.K. Tiwari).

https://doi.org/10.1016/j.heliyon.2021.e06181
Received 9 November 2020; Received in revised form 3 December 2020; Accepted 29 January 2021

virus to be prone to seasonal fluctuations, further confirming that the virus shall sustain for longer in colder temperatures. Correspondingly, a report based on India, opines that decrease in temperature and the progression towards winters may environmentally favour the spread of COVID-19 in the country, highlighting that more research needs to be undertaken to establish the exact impact (Deccan Herald, 2020; India TV, 2020).

To contain the transmission of the virus, the affected nations' governments are taking stringent measures (like restricting people's mobility, curtailing international travels, shutdowns, lockdowns, etc.). Such measures have resulted in reduced economic activities, slowed production of goods and services, business risks, declined exports, reduced trade, financial mismanagement, leading to an adverse effect on the national and global economy. The unexpected changes in the cash flows of these operations affect the value of the currency, hence giving adverse shocks to foreign exchange rates (Chang et al., 2020; Gunay, 2020). Additionally, global operations and interdependence of financial markets across nations have been severely hit due to sudden changes in demand and supply in the economy. This has hampered stock indices across the world (Liu et al., 2020a), which have a high correlation and more substantial spillover effects with the currency exchange markets (Sui and Sun, 2016; Walid et al., 2011).

The global financial markets have also been hit severely by oil price fall. The oil prices witnessed a sharp fall by around 30% (The Hindu, 2020). Demand for oil already weakened due to the global economic slowdown, but this weakening became worse post the pandemic outbreak. As a result of the oil price war and along with the potential impact of the virus, resulted in the worldwide major stock markets to register falls in excess of 10% (Richardson, 2020). Additionally, the fears over the dramatic news of infections and patient deaths cases coming specially from Italy, France and Spain further worsened the stock market fluctuations (Sharif et al., 2020). This unfortunate situation created by COVID-19 makes it necessary to examine the impact of pandemic outbreak on the economy of the affected nations. Fluctuations in China's stock market might have spillover effects on the stock markets of other nations due to the interdependence among the contemporary economies (He et al., 2020).

Two contexts – related to environment and financial markets – motivated by the strands in existing literature, drive the motivation of this study. One, the recent studies use time-series data, employing various models (Generalized Additive Model or GAM, Susceptible Exposed Infectious Recovered model or SEIR, etc.) to study the role of temperature on COVID-19 cases but fail to confirm the association strongly. For example, Kumar (2020) and Xie and Zhu (2020) conclude a positive linear relationship between temperature and COVID-19 confirmed cases. Results by Auler et al. (2020), Oliveiros et al. (2020) and Qi et al. (2020) report higher temperature to favour the spread of COVID-19 virus. Whereas Prata et al. (2020) and Quilodran et al. (2020) show a negative association of temperature and confirmed COVID-19 cases. Similar case is evident in Brazil where temperature had a negative linear relationship with the number of confirmed cases (Pequeno et al., 2020; Sarkodie and Owusu, 2020). Hence, during such uncertain times, the literature is inconclusive about the role of temperature in the spread of COVID-19 virus. Two, the economic aspect of COVID-19 is associated with financial markets Goodell (2020) and Yarovaya et al. (2020a, b). In the context of currency exchange markets, Iqbal et al. (2020) find negative coherence between the Chinese Yuan exchange rate and COVID-19 cases, using Wavelet analysis, whereas Villarreal-Samaniego (2020) employed ARDL estimations to show a close relationship between the exchange rate and the COVID-19 variables. Liu et al. (2020a) evaluate the short-term impact of the coronavirus outbreak on 21 leading stock market indices using the event study method, Sharif et al. (2020) used the Wavelet coherence method to establish the impact of the COVID-19 outbreak and oil price shocks on the US stock price index, while Aloui et al. (2020) employed the same technique to study the co-movement between the pandemic outbreak and the energy futures markets. Furthermore, few recent papers examine the impact of the COVID-19 crisis on the cryptocurrency market, regarding how the safe-haven properties and correlations between these assets have changed post crisis (Conlon et al., 2020; Conlon and McGee, 2020; Goodell and Goutte, 2020; Yarovaya et al., 2020).

The novel coronavirus has led to discussions among these relationships; hence we use the methodology of Wavelet analysis to re-examine the associations among temperature, stock/currency exchange, and COVID-19 confirmed cases. A better-modelled association shall help to understand the behavior of this disease in varying weather conditions as well as its association with the stock market returns and exchange rates. The Wavelet methodology is used mostly in Geophysics and recently getting recognition in economics, environment, finance, and weather-related studies also (Afshan et al., 2018; Bouoiyour et al., 2015; Olayeni et al., 2014; Sharif et al., 2020). Such a methodology has not been employed extensively in studies related to COVID-19. The unfamiliar situation of COVID-19 offers us to assess the pandemic's impact in two ways- First, we have examined the impact of temperature on COVID-19 cases using Wavelet coherence and phase difference. Second, by using Partial Wavelet coherence and phase difference to control for some variables, we have studied the impact of COVID-19 cases on stock market returns (and currency exchange rate) by conditioning temperature and currency exchange rates (/stock market returns), and vice-versa. The application of Wavelet techniques helps us to answer the two research questions- 1) How are the causal relations between the variables?; and 2) What is the nature of cyclicality between the variables analyzed?

Our study documents the relationship between weather (temperature), economy (stock and currency exchange rate), and COVID-19 outbreak (daily number of new confirmed COVID-19 cases) in the 15 most-affected countries by COVID-19 (see Table 1). These countries are widespread on the world map and belong to four continents- North and South America, Europe, and Asia. To examine the dependence between these variables, we rely on Wavelet methods, which can uncover potentially underlying lead-lag relationship between the weather and economy separately with daily observations of confirmed cases of COVID-19 pandemic at a different time as well as at different frequencies (Wu et al., 2020). This unique feature of localised interaction and co-movements, makes Wavelet superior when compared to traditional correlation and regression models, as the latter only tell us about an overall average relationship during the whole observation period (Fareed et al., 2020).

By establishing the relationship between COVID-19 cases and temperature, we lay down the agenda for policymakers to intervene for improving the environmental conditions, have more stringent inspections, and precise controls to tackle the COVID-19 pandemic and similar outbreaks in the future. While the lockdowns and restrictions on economic activities across the world have led to a reduction in the pollution levels while also causing an economic slowdown, policymakers would do well to take it forward from there and launch interventions to control or optimize temperature and contain the transmission of the virus (Huang et al., 2020). By analyzing the association of COVID-19 cases and stock/currency exchange rates, we provide useful insights into the literature of financial markets in the context of spillover effects. Sharif et al. (2020) analyze the coherence between the COVID-19 cases, oil price volatility, stock market returns, geopolitical risk and economic uncertainty in the US using the wavelet-based approach, while Fareed et al. (2020) examine the coherence between COVID-19 death cases, humidity and air quality index in Wuhan, China. Following the works of Sharif et al. (2020) and Fareed et al. (2020), this study adds to the literature, as it implements the wavelet coherence technique to explore the unexpected outbreak effects of the global pandemic on the temperature, exchange rates and stock market returns, collectively. Furthermore, unlike the previous studies, this study implements a much rigorous approach by evaluating a greater number of countries (i.e. top 15 most infected countries) instead of concentrating on a single country and also

Table 1. List of 15 most affected countries by COVID-19 covered in the study.

S. No.	Affected countries	Confirmed cases	Death cases
1	United States	1467884	88754
2	Russia	272043	2537
3	United Kingdom	240161	34466
4	Brazil	233142	15633
5	Spain	230183	27563
6	Italy	224760	31763
7	France	179630	27532
8	Germany	173722	7881
9	Turkey	148067	4096
10	Iran	118392	6937
11	Peru	88541	2523
12	India	85940	2752
13	China	82947	4634
14	Canada	75864	5679
15	Belgium	54989	9005

Source: (CNA, 2020).
Note: The numbers of confirmed cases and death cases are as on 17^{th} May 2020.

considers the extant data spread over a period of several months with higher infection rate. Apart from theoretical contribution, this paper will be beneficial to investors and policymakers as they perceive coronavirus risk and shape the nation's economy and stock market behavior.

Our results are triple fold- First, the wavelet coherence (WC) between the number of confirmed COVID-19 cases and temperature reveals that on the majority of occasions, there is evidence of cyclicality (in-phase) between the variables, and in most of the countries, temperature leads the relationship. Second, the partial wavelet coherence (PWC) between the number of confirmed COVID-19 cases and stock market returns (SR), after conditioning for exchange rate returns (ERR) and temperature, exhibit both cyclical (in-the-phase) and anti-cyclical (out-of-phase) patterns of connection between the variables. Third, the PWC between the number of confirmed COVID-19 cases and exchange rate return (ERR), after conditioning for stock market returns (SR) and temperature indicates both cyclicality (in-the-phase) and anti-cyclicality (out-of-phase) between the variables. The rest of the study is structured as follows. The second section describes the data and methodology; the third section presents the results; the fourth section discusses the findings; and the last section offers policy implications and finally concludes the study.

2. Data and methodology

2.1. Data

We collected data for four variables, namely - COVID-19 cases, temperature, stock market and currency exchange, for a period from 1st February, 2020 to 13th May, 2020 for the fifteen most-affected countries by COVID-19. The number of daily new confirmed cases of COVID-19 is taken from 'Our world in data' (https://ourworldindata.org/grapher/daily-cases-COVID-19). The monitoring stations nearest to each country's capital were selected to denote the daily average temperature data from the 'National Centres for Environmental Information (NCEI)' (https://www.ncei.noaa.gov/access/search/data-search/global-summary-of-the-day). Data on the stock exchange and currency exchange rate of each country (details in Table 2) were extracted from 'Yahoo! Finance' (https://in.finance.yahoo.com/).

Table 2. List of stock exchange indices and currencies of selected countries.

S. No.	Affected countries	Stock exchange index (SEI)	Currency against USD
1	United States	Dow Jones Industrial Average	US Dollar (USD)
2	Russia	MOEX Russia Index	Russian Rouble (RUB)
3	United Kingdom	FTSE100 Index	Great Britain Pound (GBP)
4	Brazil	iBovespa	Brazilian Real (BRL)
5	Spain	IBEX35	Euro
6	Italy	FTSE MIB Index	Euro
7	France	France CAC 40 Stock Market Index	Euro
8	Germany	Germany DAX 30	Euro
9	Turkey	XU100	Turkish Lira (TRY)
10	Iran	Top 30 Index - Tepix Index	Iranian Rial (IRR)
11	Peru	S&P/BVL Peru General Index	Sol
12	India	NIFTY50	Indian Rupee (INR)
13	China	Shanghai SE Composite Index	Chinese Yuan (CNY)
14	Canada	S&P/TSX Composite Index	Canadian Dollar (CAD)
15	Belgium	BEL20	Euro

Source: Authors' own illustration.

2.2. Statistical methods

We analyze the coherence between temperature, stock market returns, currency exchange rates and COVID-19, using Wavelet analysis. Specifically, we study the following relationships:

1. Coherence between $COVID_{i,t}$ and $TEMP_{i,t}$;
2. Partial coherence between $COVID_{i,t}$ and $SR_{i,t}$, conditioned for $TEMP_{i,t}$ and $ERR_{i,t}$; and

2.3. Partial coherence between $COVID_{i,t}$ and $ERR_{i,t}$, conditioned for $TEMP_{i,t}$ and $SR_{i,t}$

$COVID_{i,t}$ represents the number of daily new confirmed cases of COVID-19, $TEMP_{i,t}$ represents daily average temperature, $SR_{i,t}$ is the daily stock market returns, and $ERR_{i,t}$ is the daily closing price of the exchange rate of the currency of the country *i* at day *t*, respectively.

The existing literature uses various approaches to investigate the nexus between the variables mentioned above. Nevertheless, there has only been a limited focus on frequency transformations when examining these linkages. Since this is a novel virus, many uncertainties still revolve around this virus. Therefore, formulating policy directions via usual methods may not be appropriate. To capture the nexus between temperature, stock/currency exchange rates, and confirmed cases of COVID-19, the use of sophisticated technique seems substantial to depict this relationship at different times and frequencies. Thus, we employ a better-modeled technique – Wavelet analysis using both WC and PWC, which helps understand the behavior of this disease in varying weather conditions. Such an understanding of the disease is pivotal to save more human lives by taking preventive measures. In multiple time series analysis, there are several advantages of using the Wavelet approach– that allows cross-analytics (Lyashenko et al., 2020); enables local analysis (Afshan et al., 2018); can be applied even if the series is non-stationary, has non-normal distribution and non-linear relations (Benhmad, 2012). Also, it captures bi-directional (lead-lag) relationships at the same time between different time-frequency combinations (Tiwari et al., 2019).

2.3.1. Wavelet coherence (WC)

The relationship between the temperature and COVID-19 confirmed cases can be encircled across time-scales through a refined methodology of Wavelet coherence (regardless of the time series). The Wavelet coherence can identify the particular areas in the time-frequency domain where abrupt and significant changes occur in the co-movement patterns of the observed time-series and are similar to traditional correlation. Aguiar-Conraria et al. (2008) define Wavelet coherence as 'the ratio of the cross-spectrum to the product of the spectrum of each series, and can be thought of as the local (both in frequency & time) correlation between two time-series'. Abiding Torrence and Webster (1998), we define the Wavelet coherence between two-time series as:

$$R_s^2(k) = \frac{\left|K\left(k^{-1}M_s^{xy}(k)\right)\right|}{K\left(k^{-1}\left|M_s^x\right|^{\frac{1}{2}}\right).K\left(k^{-1}\left|M_s^y\right|^{\frac{1}{2}}\right)}, \quad (1)$$

where K is a smoothing operator and $M_s^{xy} = E[M_s^x \tilde{M}_s^y]$ is the cross-spectrum, with $\tilde{M}_s^y$ as the complex conjugate of M_s^y. Here, $0 \leq R_s(k) \leq 1$, which is similar to the traditional correlation coefficient (ρ) $0 \leq (\rho) \leq 1$. Without smoothing, coherency is identically one at all scales and times. We may further write the smoothing operator K as a convolution in time and scale:

$$K(M) = K_{scale}(K_{time}(M_s)) \quad (2)$$

where K_{scale} denotes smoothing along the Wavelet scale axis and K_{time} denotes smoothing in time. The time convolution is done with a Gaussian model, and the scale convolution is performed with a rectangular window (Torrence and Compo, 1998).

2.3.2. Partial wavelet coherence (PWC)

In this methodology, the co-movements are studied between two variables while controlling for the common effects of a third variable. For PWC transform (Aguiar-Conraria and Soares, 2011), define coherence as:

$$R_s^2(K)_{XY|Z} = \frac{\left|Q_{XY}^S\right|^2}{Q_{XX}^S \cdot Q_{YY}^S} \quad (3)$$

where Q_{XY}^S, Q_{XX}^S, Q_{YY}^S are minors associated with the smoothed cross Wavelet transforms $\left|K(k^{-1}M_s^{XY}(k))\right|^2$, $K(k^{-1}\left|M_s^X\right|^2)$ and $K(k^{-1}\left|M_s^Y\right|^2)$, respectively, in a 3 × 3 matrix Q. This trivariate model was used by Ng and Chan (2012) and is a specific form of the multivariate case, where the effects of all other variables are removed from the coherence between X and Y. It is important to conceptualize the lead-lag relationship between two-time series. This is achieved by computing the phase difference, which is useful to characterize the phase relationship between any two-time series.

A phase difference of zero (0) indicates that the time series move together at the specified frequency (Figure 1). If it is between [0, π/2], then the series moves in phase, with the time series y leading x. On the other hand, if it is between [-π/2, 0], then x leads y. We have an anti-phase relation (analogous to negative covariance) if we have a phase difference of π [or −π], meaning if the phase difference is between [π/2, π], then x is leading, and the time series y is leading, if it is in between [-π, - π/2].

3. Findings

We analyze the coherence between the reference variables using WC and PWC analysis. Our results are presented in Figures 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13, 14, 15, and 16. The horizontal axis (X-axis) represents the daily sample period from 1st February 2020 to 13th May 2020. The vertical axis (Y-axis) deals with the frequency domain. The analysis considers four frequency cycles. The first two cycles (1–2 and 2–4 day bands) are associated with the short run or high-frequency bands, and the last two cycles (4–8 and 8–16 day bands) are associated with the long-run analysis or low-frequency bands. The color spectrum indicates the intensity of the co-movement between the variables under study. The blue color signifies no co-movement, while the red color means high positive co-movements between the variables. The black cone lining, known as

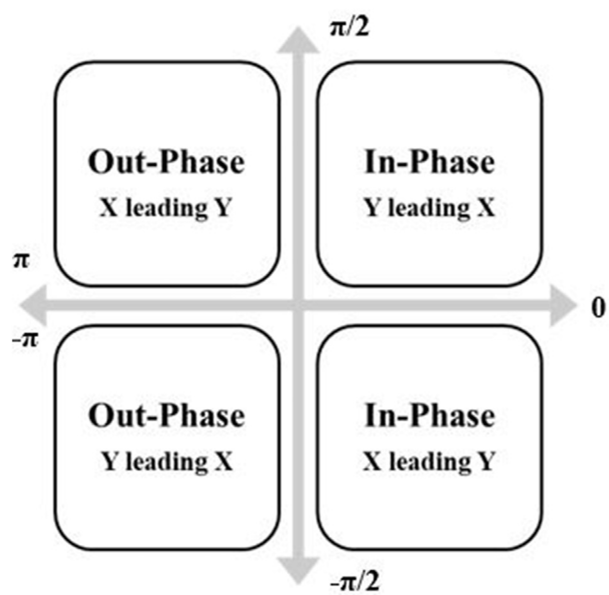


Figure 1. Phase-difference matrix**.** Note: For more details, see Aguiar-Conraria and Soares (2011).

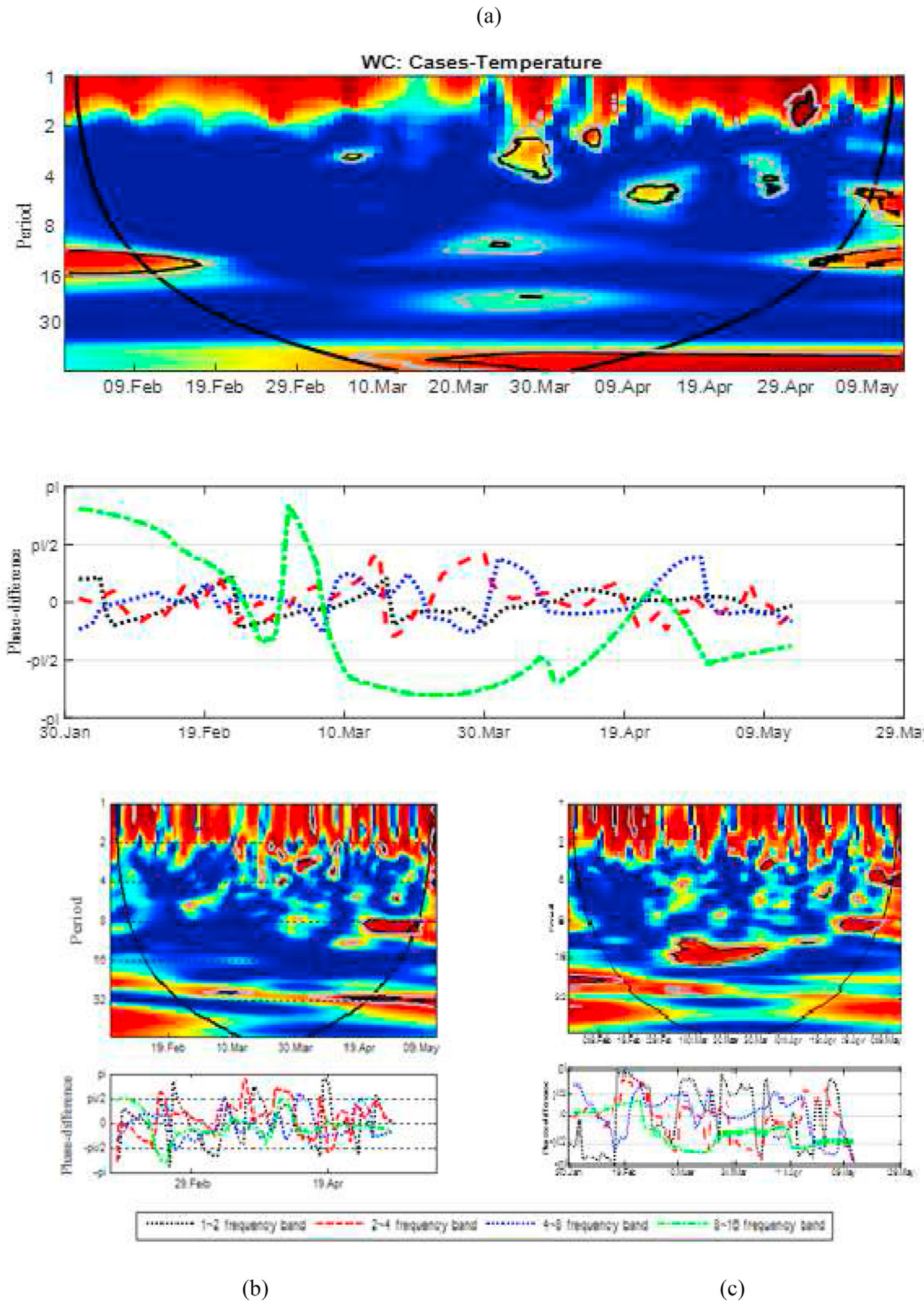


Figure 2. Belgium. (a): WC: Cases - Temperature. (b): PWC: Cases-SR| ERR-Temp. (c): PWC: Cases-SR| ERR-Temp.

the cone of influence (COI), represents the significance level, where the thick black line and the thick grey line highlighted inside the COI represent 5% and 10% level of significance, respectively. Hence, the wavelet coefficients estimates located within the cone of influence are reliable and statistically significant at 95% and 90%, while all the areas outside the cone are out of consideration.

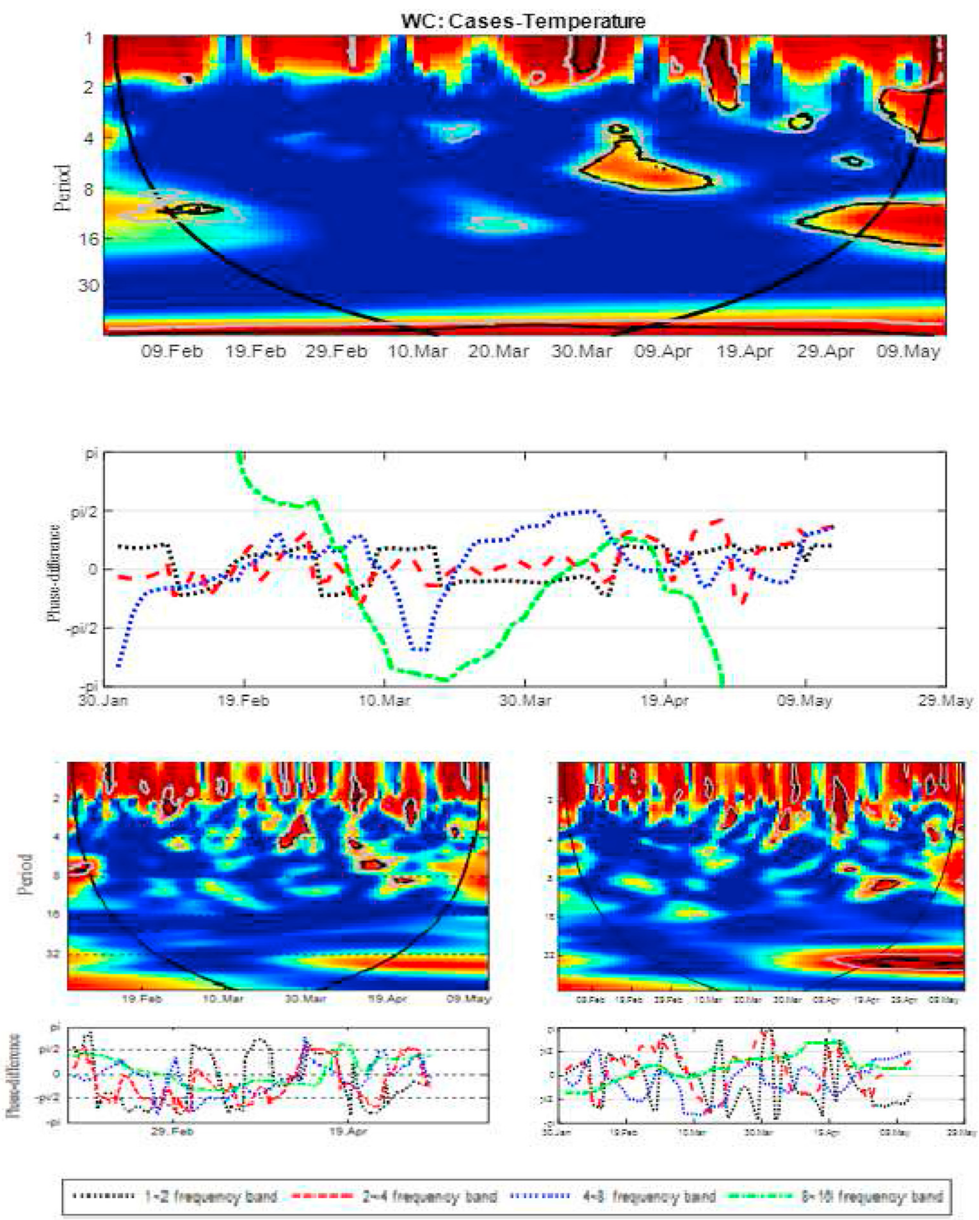
3.1. Wavelet coherence: cases – Temperature

Figures 2 (a), 3(a), 4(a), 5(a), 6(a), 7(a), 8(a), 9(a), 10(a), 11(a), 12(a), 13(a), 14(a), 15(a) and 16 (a) present Wavelet Coherence and phase difference between the number of COVID-19 cases and temperature for the 15 countries under study (interpreted in Table 3).

In Belgium, most cases report variables to be in-the-phase (0, $\pi/2$). In 1–2 day bands, the dark island between 29th April – 5th May, exhibits the variable to be in-the-phase (0, $\pi/2$), with COVID-19 cases leading. A similar case is evident by the large island between 25th – 30th March in the 2–4 day bands, while in the long-run, another island between 9th-17th April, exhibits the variables to be in-the-phase (0, -$\pi/2$), but with temperature leading over COVID-19 cases.

A small but significant coherence at 5% and 10% is visible in Brazil in the short-run (1–2 day bands) around 12th February, revealing the variables to be in-the-phase (0, $\pi/2$) with COVID-19 cases leading. In the 4–8 day bands, the large island visible between 28th March – 18th April, indicates variables to be in-the-phase with the cases leading. Furthermore, the majority of co-movements

(a)



(b) (c)

Figure 3. Brazil. (a): WC: Cases - Temperature. (b): PWC: Cases-SR| ERR-Temp. (c): PWC: Cases-ERR| SR-Temp.

between the variables in the long-run indicate COVID-19 cases to be leading.

For Canada, our findings reveal the variables to be in-the-phase in the majority of the cases. In 4–8 day bands, a huge island visible between 7th April to 23rd April, indicates significant coherence at 5% and 10%, with variables being in-the-phase (0, π/2) and cases leading. Another huge island between 9th April to 3rd May in the 8–16 day bands, the variables exhibit a significant coherence, being out-of-phase (-π/2, -π) and cases leading again.

Majority of the events in China, exhibit the variables to be in-the-phase. However, a small island around 5th May in 1–2 day bands and a huge dark island present in both the 2–4 and 4–8 day bands, exhibit the variables to be in-the-phase (0, -π/2), with temperature leading over the cases. Alternatively, in the 8–16 day bands, the small islands exhibit the variables to be out-of-phase (-π/2, -π), with cases leading.

For France, most events reveal the variables to be in-the-phase (0, π/2). In the short-run, the dark portion between 9th – 19th April, that expands from the short-run day bands to the long-run day bands, exhibits the same result throughout with variables being in-the-phase (0, π/2) and cases leading. Furthermore, small circle round 5th – 9th April in 8–16 day bands, indicates the variables to be out-of-phase (-π/2, -π), but with the cases leading.

Regarding Germany, the majority of events exhibit the variables to be in-the-phase (0, π/2) with cases leading. In 1–2 day bands, the set of dark portions between 18th March to 8th April, exhibit the variables in-the-phase (0, π/2) with cases leading. However, in the 8–16 day bands, events between 10th - 20th March reveal the variables to be out-of-phase (-π/2, -π) but with cases leading.

For India, the variables are found to be in-the-phase (0, -π/2) in most cases. However, in the short-run, the dark area between 5th – 17th April

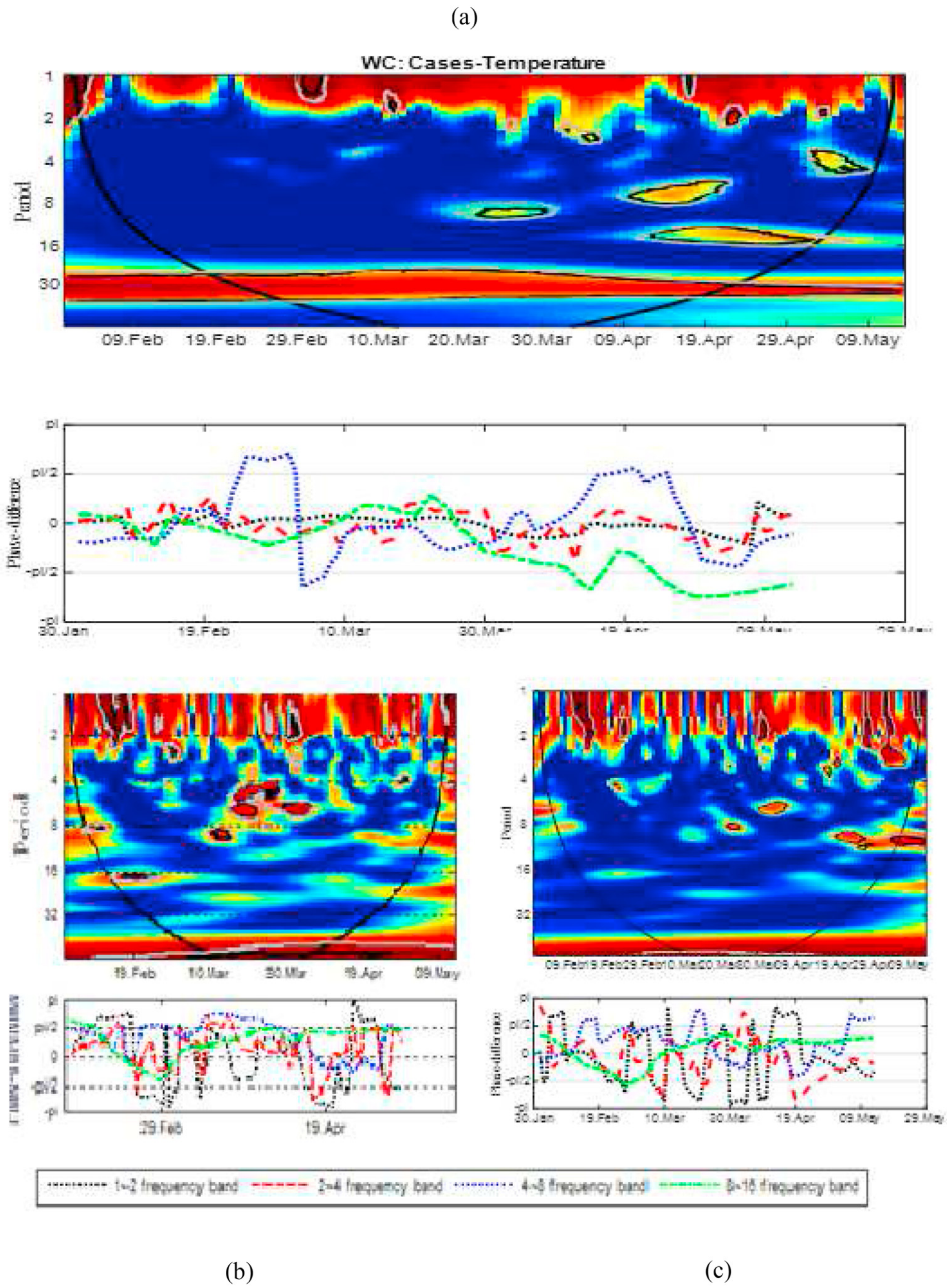


Figure 4. Canada. (a): WC: Cases - Temperature. (b): PWC: Cases-SR| ERR-Temp. (c): PWC: Cases-ERR| SR-Temp.

exhibit the variables to be in-the-phase (0, $\pi/2$) with cases leading. While the dark circles around 5th March and 15thApril indicate variables to be in-the-phase (0, -$\pi/2$) with temperature leading. A similar result is also evident by the green circle around 5th March in the 8–16 day bands.

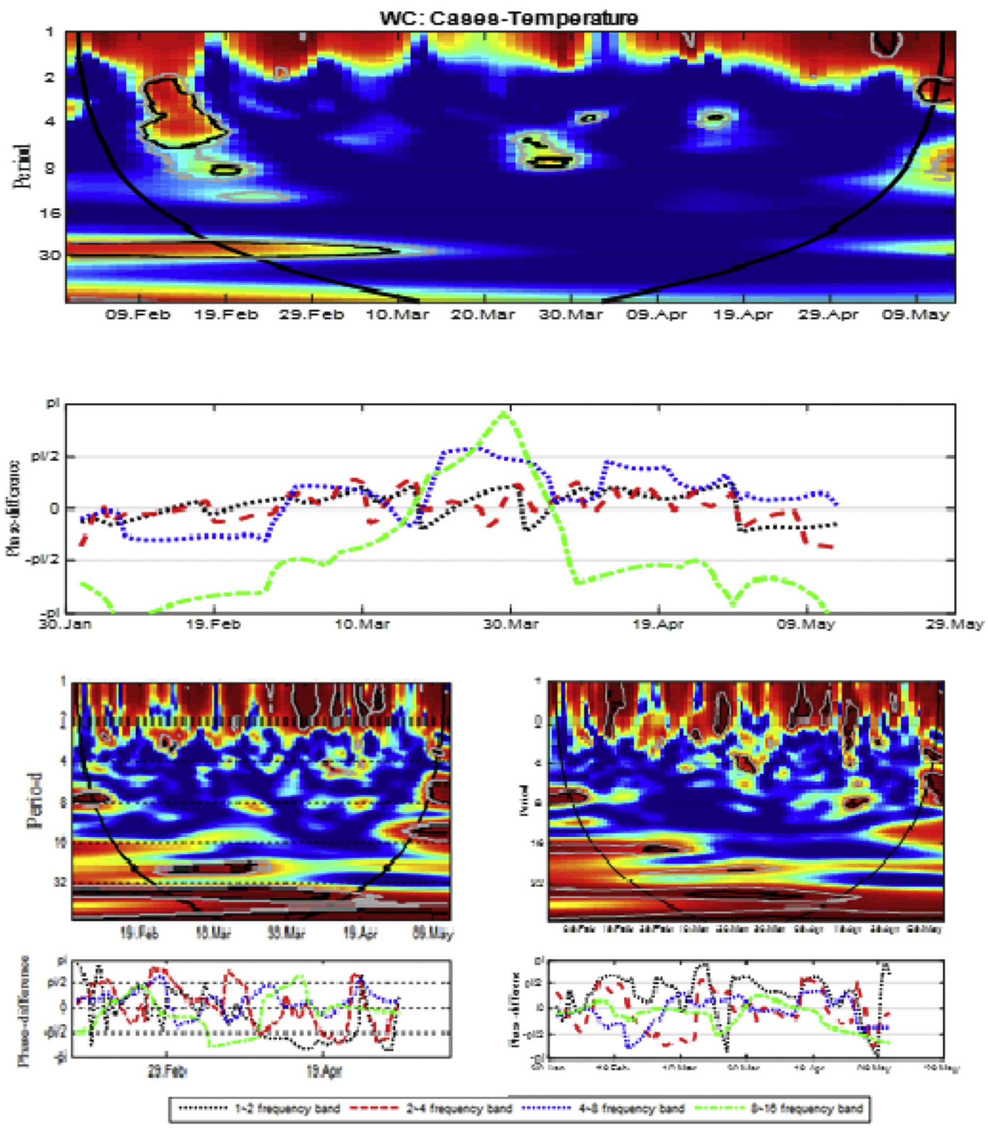
In Iran, under all events, series moves in-phase where the majority of the co-movements between the variables report temperature as the leading variable. In short-run, the most extended island from 2nd - 8th April (2–4 day bands) shows significant coherence at 5% and 10%, whereas in the long-run, the biggest island exhibits coherence from 19th - 27th April (4–8 day bands).

In Italy, majority of the events are found to be in-the-phase. In the short-run the co-movements between the variables show temperature as the leading (0, $\pi/2$) whereas in the long-run Covid-19 cases are leading. The biggest island (coherence at 5% significance) in short-run is visible from 22nd - 28th March and in the long-run, the longest island is exhibited from 12th - 31st March.

In Peru, under all the events, series moved in-the-phase where the majority of the co-movements between the variables report COVID-19 cases leading (0, $\pi/2$). In the short-run, many small islands are visible whereas in the long-run big islands ranging from 12th – 20th April and 23rd – 29th April (both in 4–8 day bands) are visible, each exhibiting coherence at 5% significance.

In Russia, majority of the series move in-the-phase with equal chances of temperature and COVID-19 cases leading both in the short-run and long-run. The short-run day bands exhibit small islands (coherence between variables at 5% and 10% significance level), whereas in the long-run, the islands appear bigger. The biggest island extends in 4–8 day bands, COVID-19 cases leading (0, $\pi/2$) from 22nd April to 9th May.

(a): WC: Cases - Temperature



(b): PWC: Cases-SR| ERR-Temp

(c): PWC: Cases-ERR| SR-Temp

Figure 5. China (a): WC: Cases - Temperature (b): PWC: Cases-SR| ERR-Temp. (c): PWC: Cases-ERR| SR-Temp.

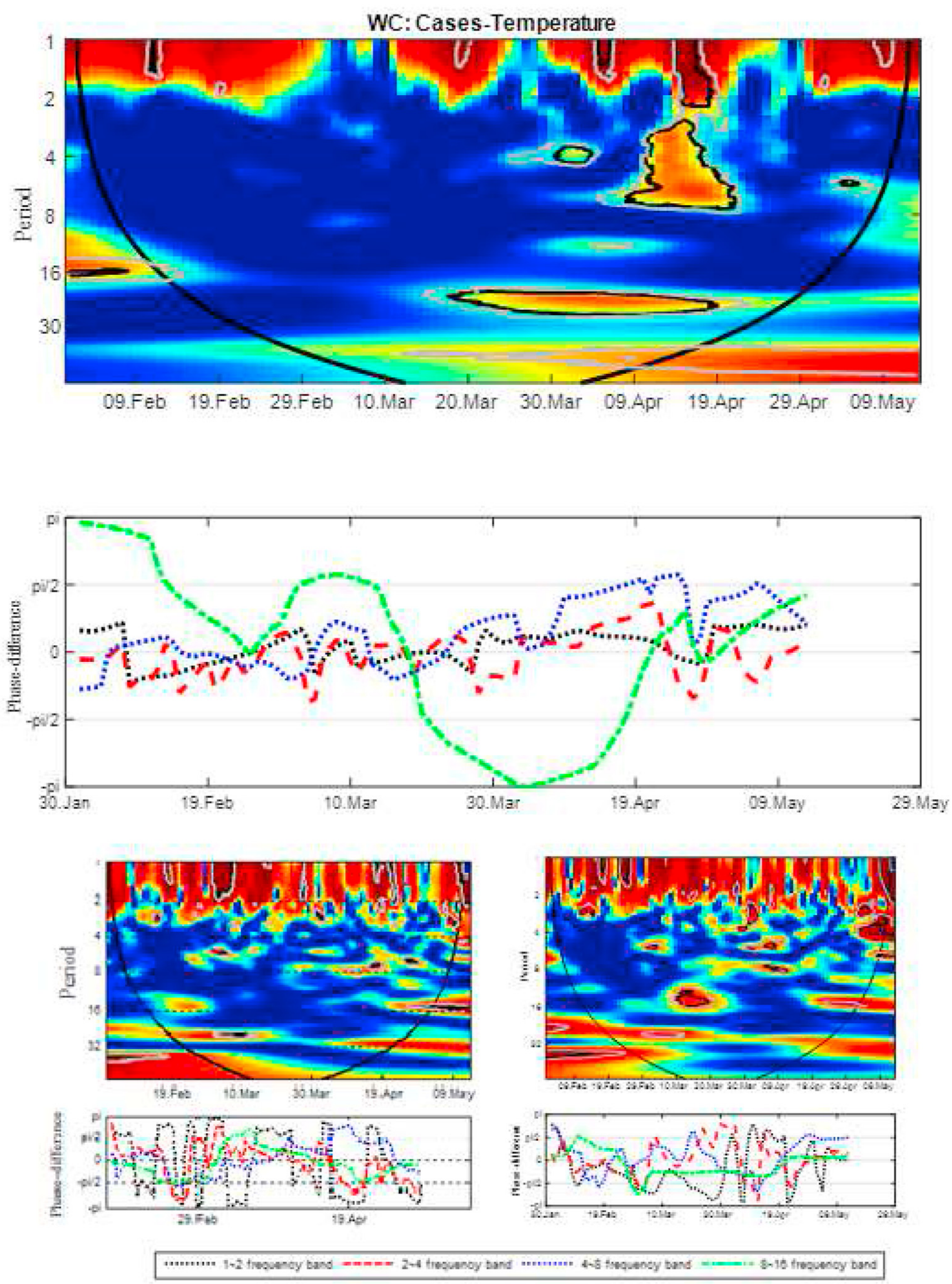
In Spain also, all the series move in-the-phase with no significant coherence in the 8–16 day bands of the long-run. The short-run day bands exhibit bigger islands when compared to those in the long-run (4–8 day bands). In the long-run, under 4–8 day bands, significant coherence is visible with smaller islands around 11th -14th March, 28th -30th March, 2nd – 6th April, 23rd – 30th April and 1st – 2nd May, where the variables are in-the-phase (0, π/2) with temperature leading the COVID-19 cases.

For Turkey, majority of events indicate significant coherence at 5% and 10%, with the variables being in-the-phase (0, -π/2). In the short-run, the dark areas around 12th March and 5th-11th May, exhibit the variables to be in-the-phase (0, -π/2) with temperature leading. Furthermore, the huge yellow circle between 20th- 30th March, extending between 2-4 and 4–8 day bands, indicates the variables to be in-the-phase (0, -π/2), with temperature leading again.

Concerning UK, all the events exhibit a strong co-movement between the variables being in-the-phase, but the majority of them indicate the variables to be in-the-phase (0, -π/2), with temperature leading. In 1–2 day bands, the dark areas around 25th March and 13th April exhibit variables to be in-the-phase (0, -π/2), with temperature leading. However, another dark area around the end of the sample period indicates the variables to be in-the-phase (0, π/2), but with cases leading.

For the US, the majority of the events reflect upon the variables to be in-the-phase (0, -π/2), with temperature leading over the number of COVID-19 cases. In the 2–4 day bands, the grey circles around 25th February and 5th April, exhibit the variables to be in-the-phase (0, π/2), with cases leading. However, in 4–8 day bands, the temperature again leads with variables being in-the-phase (0, -π/2).

(a)



(b) (c)

Figure 6. France. (a): WC: Cases - Temperature. (b): PWC: Cases-SR| ERR-Temp. (c): PWC: Cases-ERR| SR-Temp.

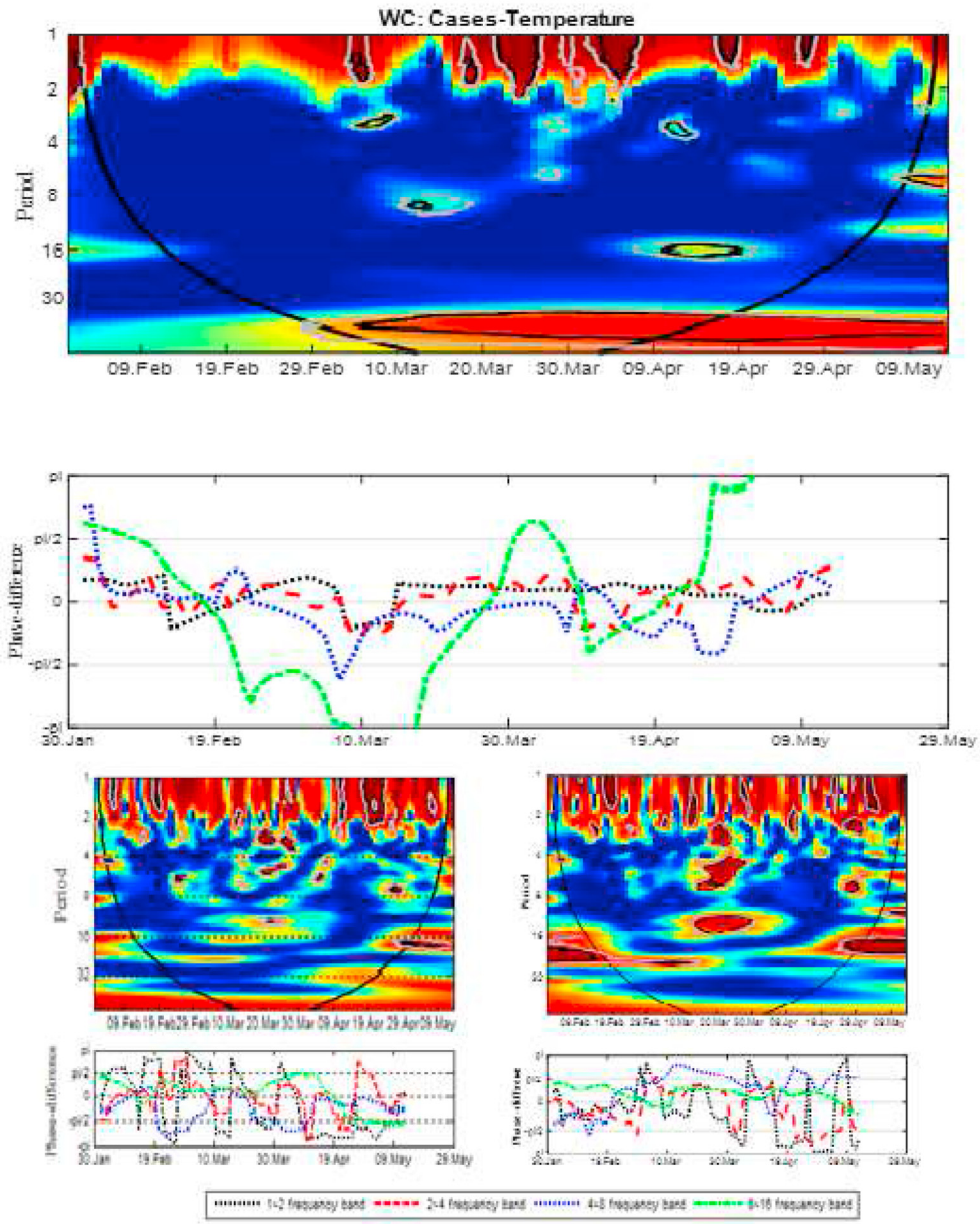
Overall, the coherence between the COVID-19 cases and temperature is observed to be stronger at lower frequency bands for all the 15 countries under study, indicating significant co-movements between temperature and COVID-19 pandemic outbreak that shall sustain for a long period of time. However, the same coherence between the variables is weaker over the short-term. Apart from cyclicality between the variables, most of the events in the infected countries imply that the average daily temperature shows a positive coherence with the daily number of confirmed COVID-19 cases.

3.2. Partial wavelet coherence (PWC): Cases-SR| ERR-Temperature

Figures 2 (b), 3(b), 4(b), 5(b), 6(b), 7(b), 8(b), 9(b), 10(b), 11(b), 12(b), 13(b), 14(a), 15(b) and 16b present the Partial Wavelet Coherence (PWC) and phase difference between the number of confirmed COVID-19 cases and stock-market returns for the 15 countries under study (as interpreted in Table 4), while controlling for the impact of the additional factors namely, currency exchange rates and temperature.

In Belgium, the variables are out-of-phase (-π/2, -π) in the short-run (1–2 day bands), around the 5th of April, 2020, indicating the COVID-

(a)



(b)   (c)

Figure 7. Germany. (a): WC: Cases - Temperature (b): PWC: Cases-SR| ERR-Temp. (c): PWC: Cases-ERR| SR-Temp.

19 cases to be leading. For both the long run day bands, the variables are in-the-phase (0, -π/2) and SR leading. Within 8–16 day bands, a dark oval is present between 20th April – 10th May. Hence, in the majority of cases, the variables are in-the-phase.

In Brazil, the variables lie out-of-phase (π/2, π) around 10th February with SR leading for 1–2 day bands. In the short-run, majority of the events exhibit variables to be in-the-phase with SR leading. In case of 4–8 day bands, two islands between 10th – 19th April, indicate variables to be in-the-phase (0, π/2) with cases leading. Hence, a strong coherence is evident between the two variables, with variables being in-the-phase.

For Canada, in the short-run (1–2 day bands), a dark area between 10th February to 19th February, and around 30th April, indicates that the variables are highly coherent, lying out-of-phase (π/2, π), with SR leading. However, unlike previous cases, for the 8–16 day bands, islands around 9th February and 12th March, exhibit variables to be present in-the-phase (0, π/2), resulting in the cases leading. Hence, from the majority of results, it is evident that the variables are in-the-phase.

A huge island is visible in 1–2 day bands for China, around 5th April indicating the variables to be out-of-phase (-π/2, -π) and COVID-19 cases leading. The set of long islands around 15th-25th April, exhibit similar results. Over the long-run, significant co- movement is visible in the beginning and at the end of the sample period, with variables being in-the-phase (0, π/2) and the cases leading. However, in majority of events, the variables are in-the-phase.

For France, during the short-run, majority of events exhibit COVID-19 cases to be leading, while during the long-run, SR is leading. In 1–2 day bands, the dark area between 1-10th March indicates the variables to be out-of-phase (π/2, π), with SR leading, while the islands between 18th –

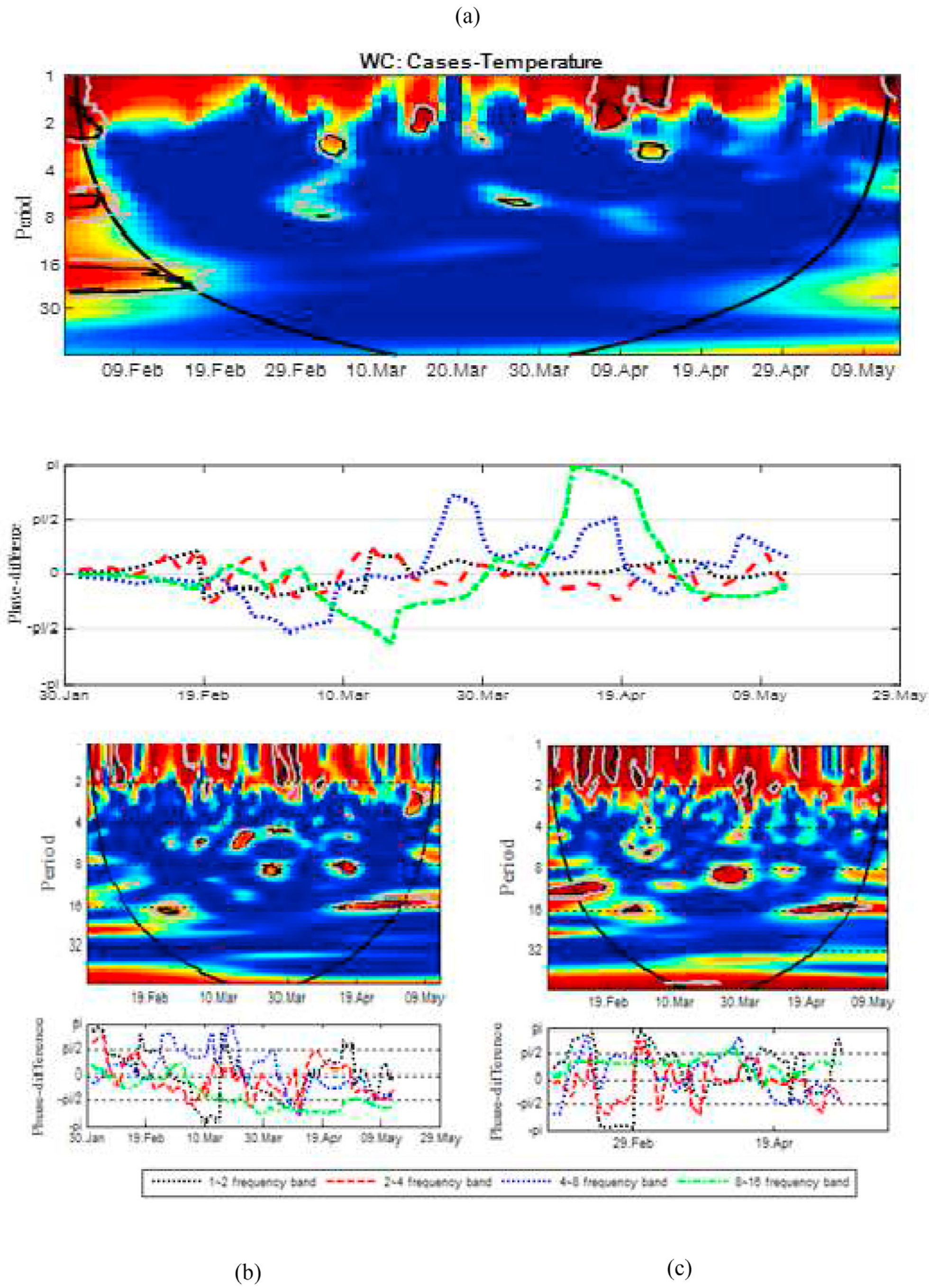


Figure 8. India. (a): WC: Cases - Temperature. (b): PWC: Cases-SR| ERR-Temp. 8 (c): PWC: Cases-ERR| SR-Temp.

22nd April exhibit variables to be out-of-phase (-π/2, -π), with cases, leading.

For Germany, majority of the events reflect the variables to be in-the-phase (0, π/2). In 1–2 day bands, the dark area around 19th February, exhibits the variables to be out-of-phase (π/2, π) with SR leading, while another shaded area between 19th – 25th March, exhibits the variables to be out-of-phase (-π/2, -π), but with the cases leading. A grey spot in the 8–16 day bands, exhibits the variables to be in-the-phase (0, π/2) with the cases leading over the stock market returns.

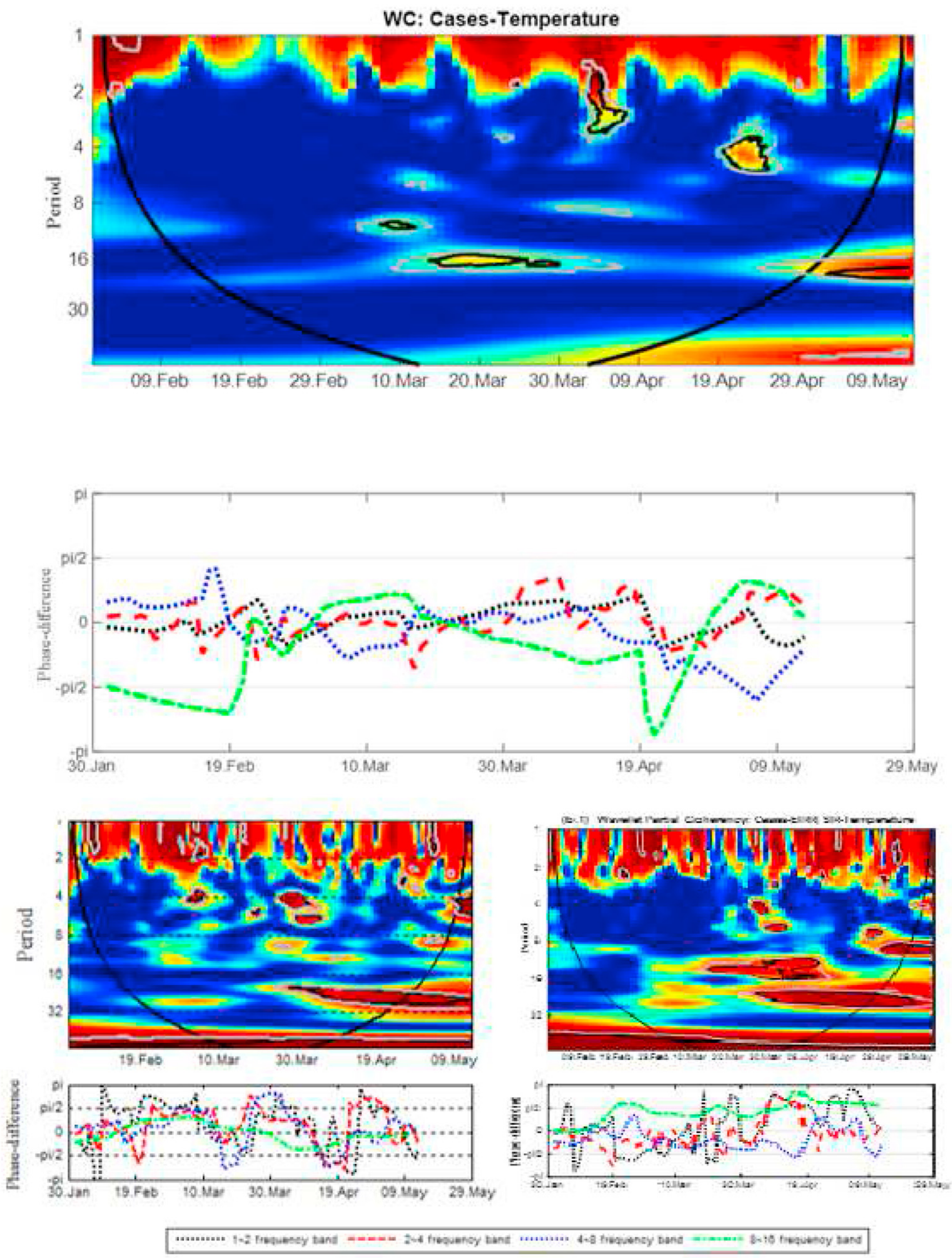
With reference to the short-run day bands for India, majority of the events exhibit the variables to be in-the-phase (0, -π/2). The set of islands between 28th March – 2nd April indicates that SR is leading. Similar case is evident by the dark island present between 15th – 20th March, in 4–8 day bands, while on the other hand, dark areas between 25th - 30th March and 15th April – 5th May exhibit the variables to be out-of-phase (-π/2, -π), with the COVID-19 cases leading.

In Iran, majority of the series move in-the-phase. In the short-run, the islands appear smaller, whereas, in the long-run, big island from 26 March to 3 April (4–8 day bands) shows coherence in out-phase with SR as the leading variable (π, π/2).

In Italy, majority of the islands fall in short-run (1–2 and 2–4 day bands) with co-movements between variables at in-the-phase and out-phase, both. The long-run exhibits bigger islands showing coherence at 5% significance level with the COVID-19 cases as leading. The majority of the events are in-the-phase.

In Peru, the majority of the series show co-movement between the variables at out-phase. The short-run exhibits more islands than that in the long-run. The biggest island (short-run) at 2–4 day bands, from 26th –

(a)



(b) (c)

Figure 9. Iran. (a): WC: Cases - Temperature. (b): PWC: Cases-SR| ERR-Temp. (c): PWC: Cases-ERR| SR-Temp.

31st March, show COVID-19 cases as leading (-π, -π/2) whereas the long-run exhibits more extended island from 22nd April – 7th May with Cases leading (0, π/2).

In Russia, majority of series show co-movement between the variables in-the-phase. The short-run witnesses many smaller islands than those in the long-run. The biggest island shows coherence at 5% from 1st – 14th April with SR leading (0, -π/2) at in-phase. 1–2 and 2–4 day bands exhibits the COVID-19 cases as leading in majority events, alternatively, in the long-run SR leads cases majorly.

In Spain, majority of the series move in-the-phase. Two big islands are visible showing coherence at 5–10% significance level. In short-run 1–2 day bands from 20th – 30th March, cases lead (0, π/2) at in-phase, whereas in the long-run, the island is similar from 20th – 28th March with SR as leading (0, -π/2) variable.

For Turkey, majority of the events indicate the variables to be out-of-phase. In the short-run, the dark area around 27th February, indicates the variables to be out-of-phase (-π/2, -π) with the COVID-19 cases leading. While in the long-run, the long dark area between 12th March – 2nd April indicates the same result in 4–8 day bands, but in 8–16 day bands, the island between 5th – 15th March, exhibits the variables to be in-the-phase (0, -π/2), with SR leading.

For UK, majority of the events over both the short and long run indicate the variables to be in-the-phase (0, -π/2). The set of islands around 28th March, 5th April, 10th April, 1st May and 9th May exhibit the

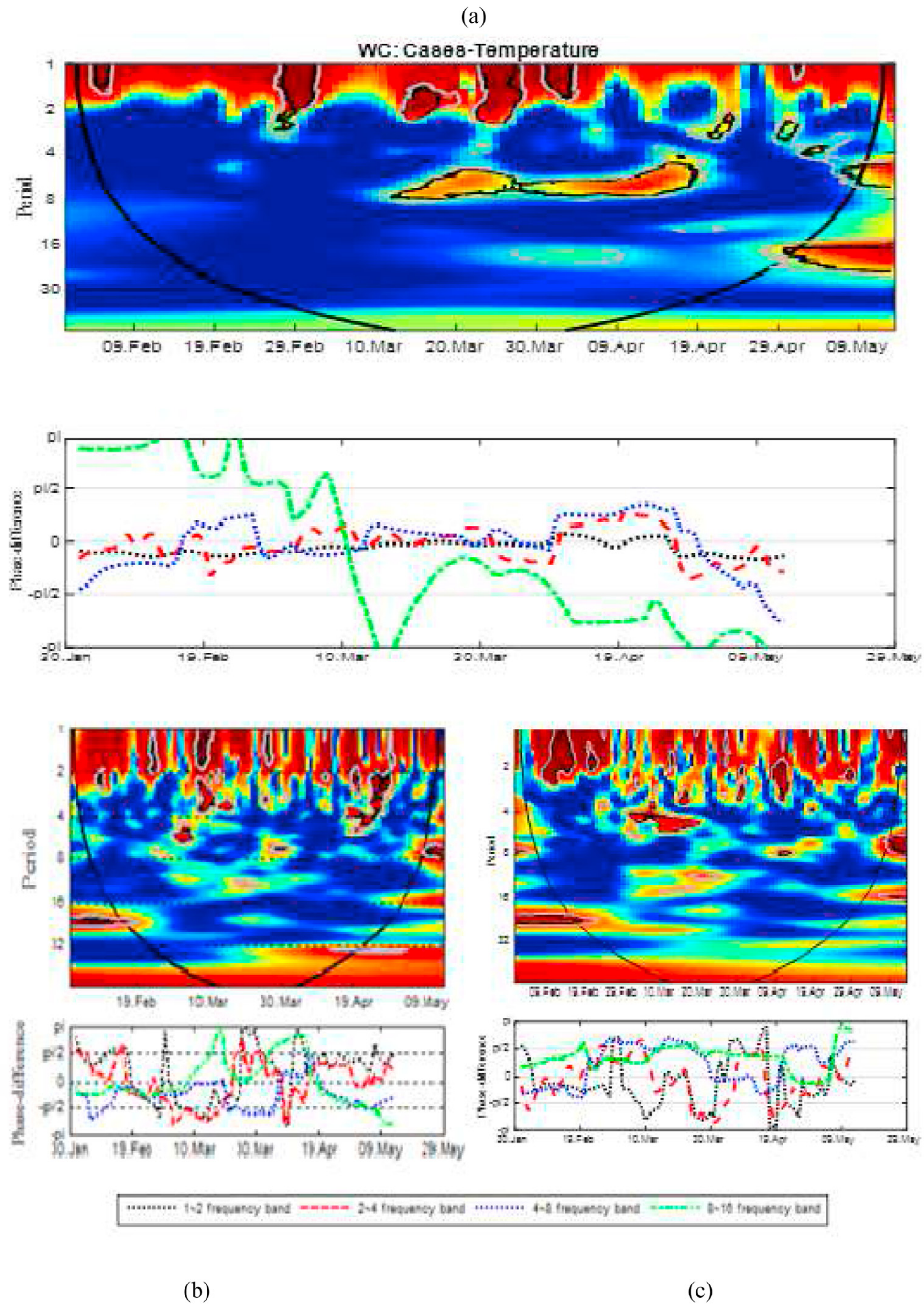


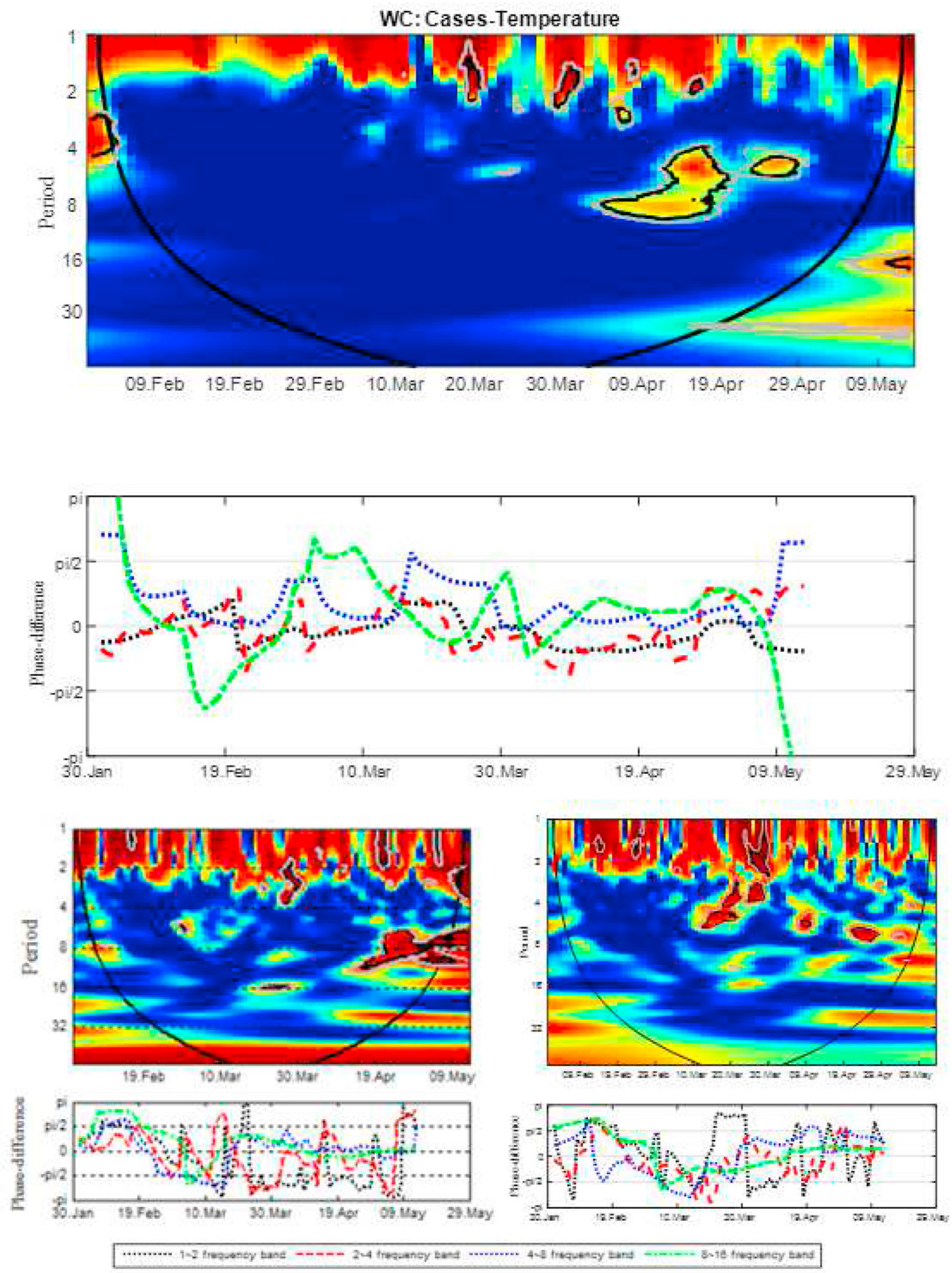
Figure 10. Italy. (a): WC: Cases - Temperature. (b): PWC: Cases-SR| ERR-Temp. (c): PWC: Cases-ERR| SR-Temp.

variables to be in-the-phase (0, -π/2) with SR leading. Similar is the case with the shaded area present around 5th May in the 2–4 day bands, while the dark area around 12th February exhibits the variables to be in-the-phase (0, π/2), with the cases leading. The large shaded area between 15th – 30th March exhibits the same result, while a small grey spot around 19th April exhibits the variables to be out-of-phase (π/2, π), with SR leading.

Concerning events in the US, strong coherence is visible between the two variables, while most events indicate the variables to be out-of-phase (-π/2, -π). In the short-run, a dark area visible around 19th April in 1–2 day bands indicates the cases to be leading, and in the long-run, the dark round island between 20th – 30th March exhibits the variables to be out-of-phase (-π/2, -π) with the cases leading again.

The PWC between the number of confirmed COVID-19 cases and stock market returns (SR), after conditioning for exchange rate returns (ERR) and temperature, exhibits short-term and long-term co-movements between the confirmed COVID-19 cases and SR. Most of the events exhibit SR leading COVID-19 cases, although the association between variables is mainly negative (-π/2, -π and 0,-π/2). There is evidence of both cyclical (in-the-phase) and anti-cyclical (out-of-phase) patterns of connection between the variables. Out of all the countries under study, the stock market returns of 9 countries, namely, Belgium, Brazil, India, Italy, Peru, Russia, Turkey, US, and UK, declined significantly (in most events) with the spread of COVID-19 cases in their regions. Furthermore, strong connectedness at low frequencies displays that COVID-19 cases have a long-term impact on the stock markets of the countries under

(a)



(b) (c)

Figure 11. Peru. (a): WC: Cases - Temperature. (b): PWC: Cases-SR| ERR-Temp. (c): PWC: Cases-ERR| SR-Temp.

study. Hence, our findings emphasize the severe long-term impact of the COVID-19 cases on the stock market indices under reference.

3.3. Partial wavelet coherence (PWC): Cases-ERR| SR-Temperature

Figures 2 (c), 3(c), 4(c), 5(c), 6(c), 7(c), 8(c), 9(c), 10(c), 11(c), 12(c), 13(c), 14(c) and 15(c) present the PWC and phase difference between the number of confirmed COVID-19 cases and currency exchange rates for the 14 countries under study (as interpreted in Table 5), while controlling for the impact of the additional factors, namely, stock market returns and temperature.

Three islands are visible in Belgium in the short-run (1–2 day bands), representing small but significant (at 5% and 10%) co-movements, with the variable being out-of-phase (-π/2, -π) and the COVID-19 cases leading between 8th – 19th February. The variables are out-of-phase (-π/2, -π), in the long-run (4–8 and 8–16 day bands) between 19th – 23rd April and between 5th March to 23rd March, respectively, verifying the COVID-19 cases as leading.

For Brazil, in the short run, significant coherence is visible, with variables being in-the-phase and COVID-19 cases leading around 19th February and 10th March. A long island extends between 10th – 15th April, in both short-run day bands indicating variables to be in-the-phase

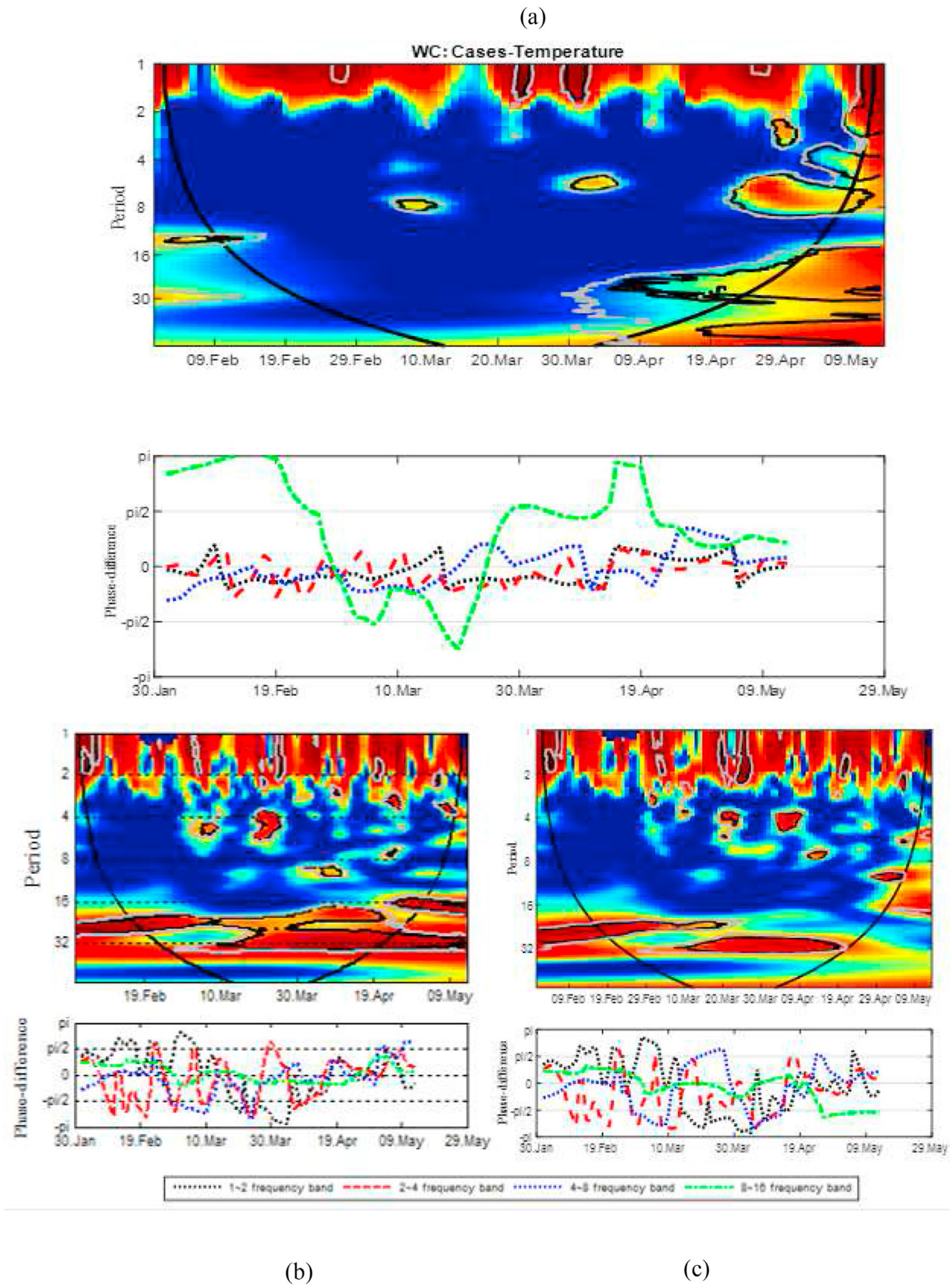


Figure 12. Russia. (a): WC: Cases - Temperature. (b): PWC: Cases-SR| ERR-Temp. (c): PWC: Cases-ERR| SR-Temp.

(0, -π/2), with cases leading. In the long-run, the variables exhibit to be in-the-phase with the cases leading and out-of-phase (π/2, π) with ERR leading.

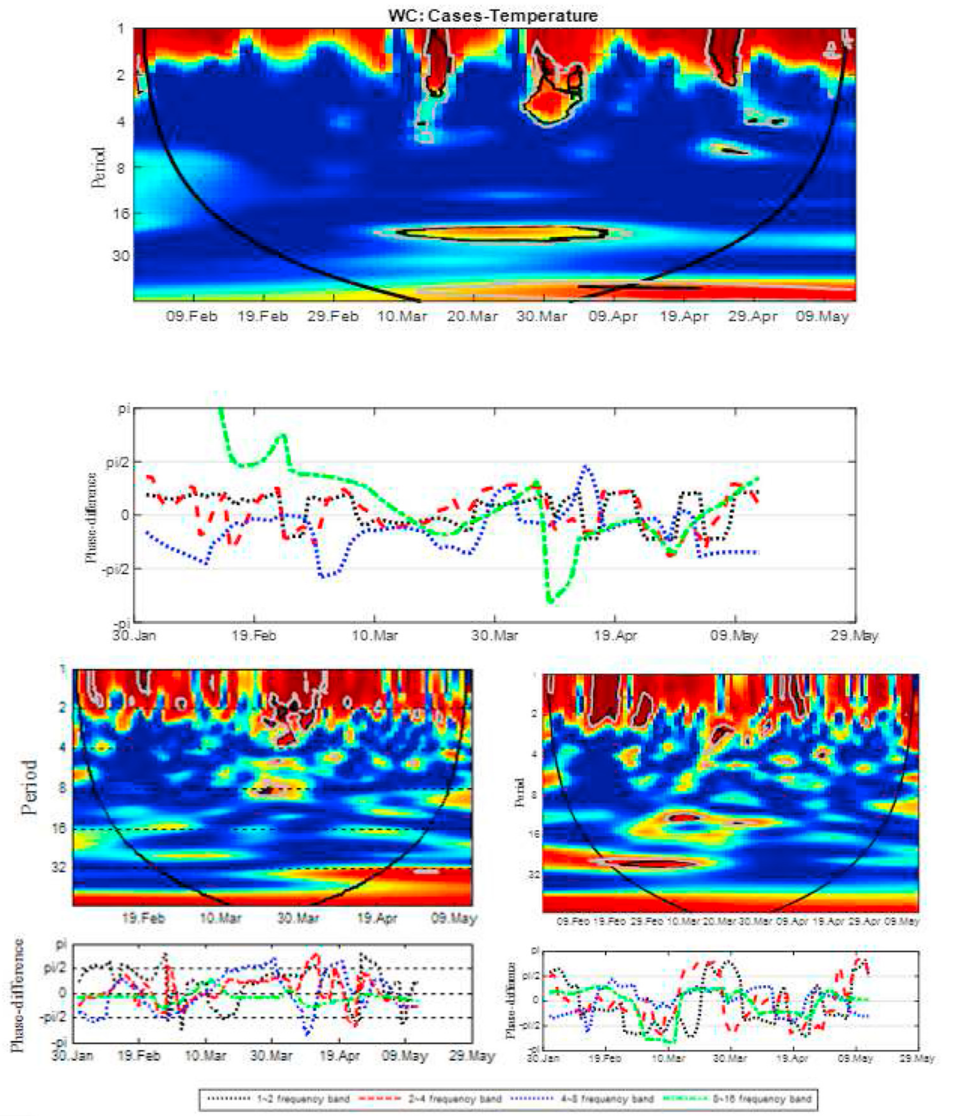
Concerning Canada, in 1–2 day bands, a dark area around 15th February that extends to 2–4 day bands, reflects significant coherence at 5% and 10% with variables being in-the-phase (0, -π/2) and ERR leading. For 4–8 day bands, the islands exhibit the variables to be in-the-phase (0, -π/2), with ERR leading, while the COVID-19 cases are leading for 8–16 day bands.

For China, majority of co-movements between the variables report to be in-the-phase. In the 1–2 day bands, significant coherence is visible around 15th February, 15th March and from 7th – 30th April, where the variables are majorly in-the-phase (0, π/2) with cases leading. For 2–4 day bands, majority of the events exhibit the variables to be in-the-phase and out-of-phase (0, π/2 and -π/2, -π), with the cases leading again.

For France, most cases exhibit the variables to be in-the-phase (0, -π/2). In 1–2 day bands, the dark areas around 19th and 25th February exhibit the variables as in-the-phase (0, -π/2) with ERR leading. However, in the 4–8 day bands, the dark area from 29th April to 13 May, exhibit the variables to be out-of-phase (π/2, π) with EER leading, and in 8–16 day bands, dark circle between 10th - 20th March, again concludes EER as leading.

For Germany, most events reveal the variables to be in-the-phase (0, π/2). In 1–2 day bands, the events around 19th February and 12th march exhibit variables in-the-phase (0, π/2) with EER leading. The huge circle between 10th – 30th March conclude ERR to be leading in 4–8 day bands and cases to be leading in 8–16 day bands.

(a)



(b) (c)

Figure 13. Spain. (a): WC: Cases - Temperature. (b): PWC: Cases-SR| ERR-Temp. (c): PWC: Cases-ERR| SR-Temp.

For India, majority of events reflect upon the variables to be in-the-phase (0, π/2). In 1–2 day bands, the dark portion reveals the variables to be out-of-phase (π/2, π) with EER leading. All the events in the long-run reveal the variables to be in-the-phase (0, π/2) with cases leading over the exchange rate returns for India.

In Iran, majority of the series move in-the-phase. In short-run, all the small islands show coherence among variables with ERR leading whereas in the long-run, the islands appear bigger and at 4–8 and 8–16 day bands the co-movement between the variables is in-the-phase.

In Italy, majority of the events show that series are out-phase. The short-run day bands exhibit more islands showing coherence at both 5% and 10% significance level, with COVID-19 cases leading whereas in the long-run, ERR leads cases majorly.

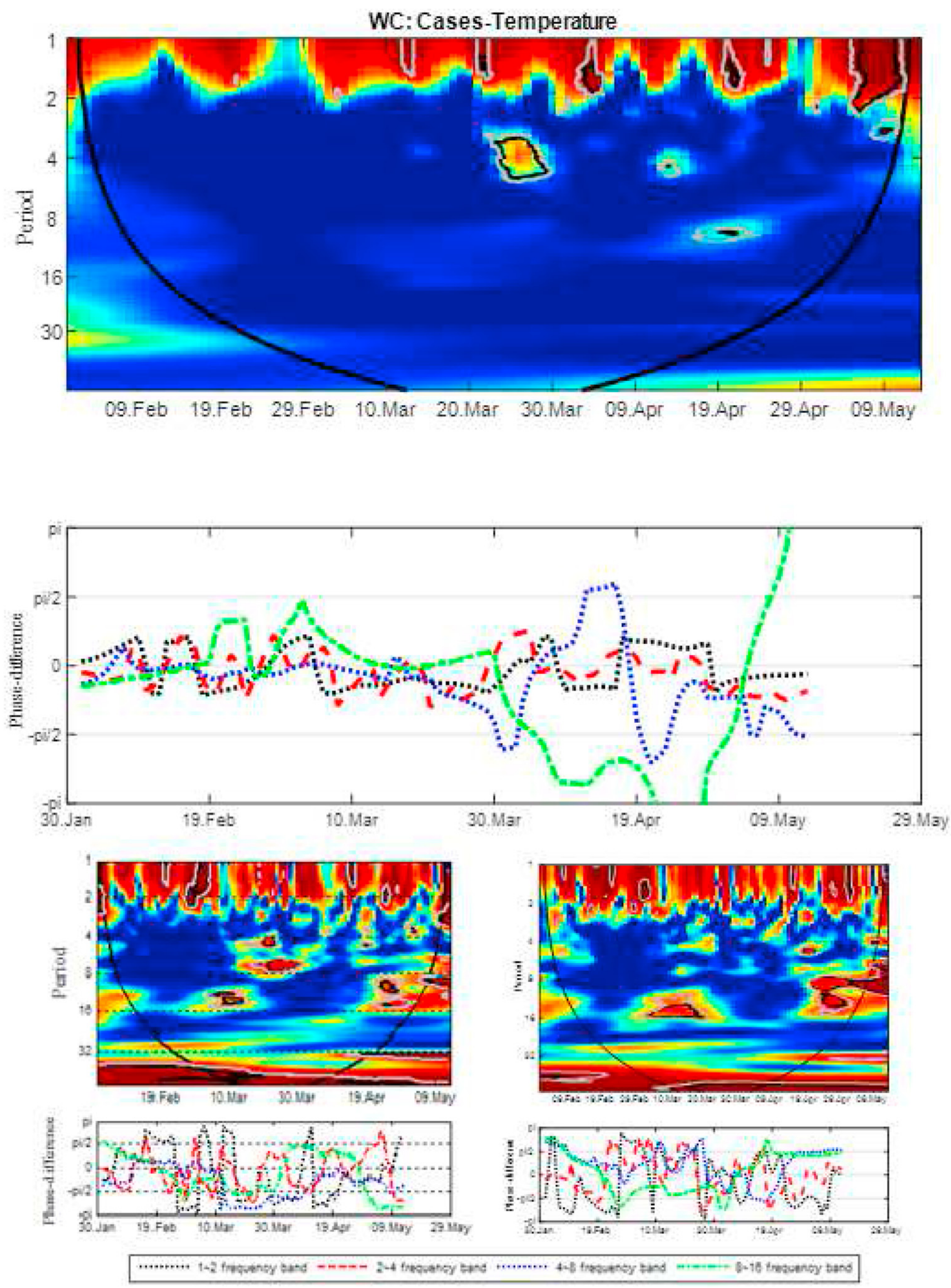
In Peru, the majority of the series are moving in-the-phase where in short-run, ERR leads cases majorly whereas in the long-run, the COVID-19 cases are leading. In short run, the biggest island is visible from 22–30 March where ERR is leading (π, π/2) at out-phase. 4–8 day bands have longest island from 12th – 22nd March with cases leading (-π, -π/2) at out-phase.

In Russia, the short-run day bands exhibit different size of islands and are much more than those in the long-run. Majority of the events have COVID-19 cases as the leading variable. 4–8 day bands witness bigger islands from 3rd – 10th April having cases as leading (-π, -π/2) at out-phase and 11th – 18th April have ERR as leading (0, -π/2) at in-phase.

In Spain, majority of the series move in-the-phase. In the short-run, maximum events report ERR as a leading variable, whereas in the long-run COVID-19 cases lead. All the islands in 1–2, 2–4 and 8–16 day bands have coherence at 5% significance level, whereas 4–8 day bands exhibit coherence at 10% significance level.

For Turkey, most events reveal the variables to be out-of-phase (-π/2, -π). In 1–2 day bands, the dark areas around 22nd February and 2nd May, exhibit the variables to be out-of-phase (-π/2, -π) with the cases leading. Around the 2nd of March, the dark circle indicates the variables to be out-of-phase (π/2, π) with ERR leading. Furthermore, the dark area in the

(a)



(b) (c)

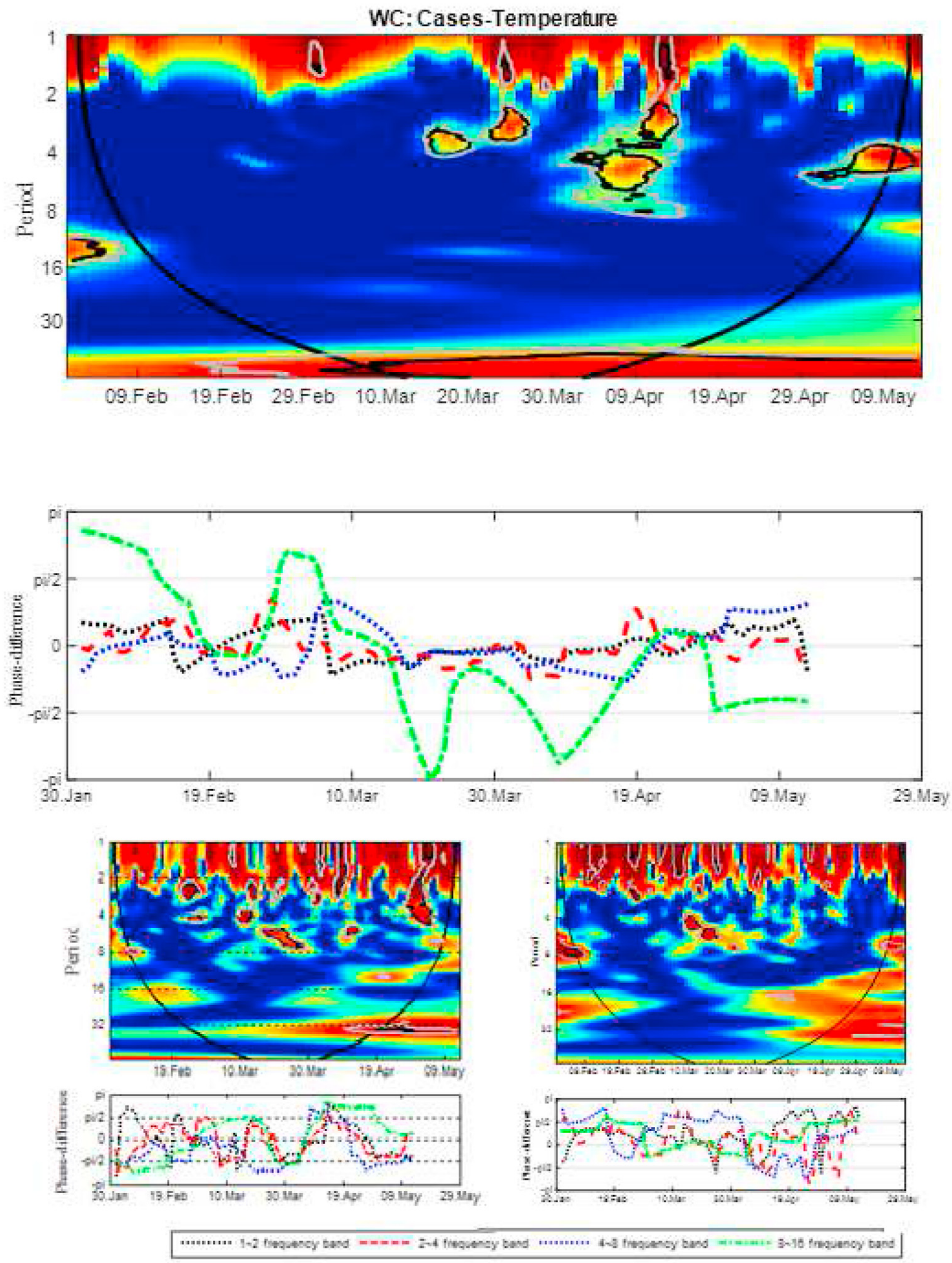
Figure 14. Turkey. (a): WC: Cases - Temperature. (b): PWC: Cases-SR| ERR-Temp. (c): PWC: Cases-ERR| SR-Temp.

8–16 day bands, from 19th April to 5th May, indicates the variables to be in-the-phase (0, π/2), but with cases leading again.

For the UK, most events indicate significant coherence, with the variables being in-the-phase (0, π/2). The set of islands between 25th to 10th February, indicate the variables to be in-the-phase (0, π/2), with the cases leading. The two islands between 10th – 30th March indicate the variables to be out-of-phase (π/2, π), with ERR leading, while another dark area around the 8th of May, indicate the variables to be in-the-phase (0, π/2), with the cases leading.

The PWC between the number of confirmed COVID-19 cases and exchange rate return (ERR), after conditioning for stock market returns (SR) and temperature, indicates that COVID-19 cases and ERR correlate or move together mostly in the short-and long-term over the sample period. Most of the events exhibit ERR leading COVID-19 cases, although there mainly exists negative coherence (0,-π/2 and -π/2, -π) between variables. There is evidence of both cyclicality (in-the-phase) and anti-cyclicality (out-of-phase) between the variables. Furthermore, out of all the countries under study, six countries, namely, Belgium, Brazil, China, India, Russia, and UK, confirm COVID-19 cases to be leading, implying that the increase in the number of COVID-19 cases has a significant effect on the volatility of these countries' currency exchange rate. Furthermore, strong connectedness at low frequencies displays that COVID-19 cases

(a)



(b) (c)

Figure 15. United Kingdom. (a): WC: Cases - Temperature. (b): PWC: Cases-SR| ERR-Temp. (c): PWC: Cases-ERR| SR-Temp.

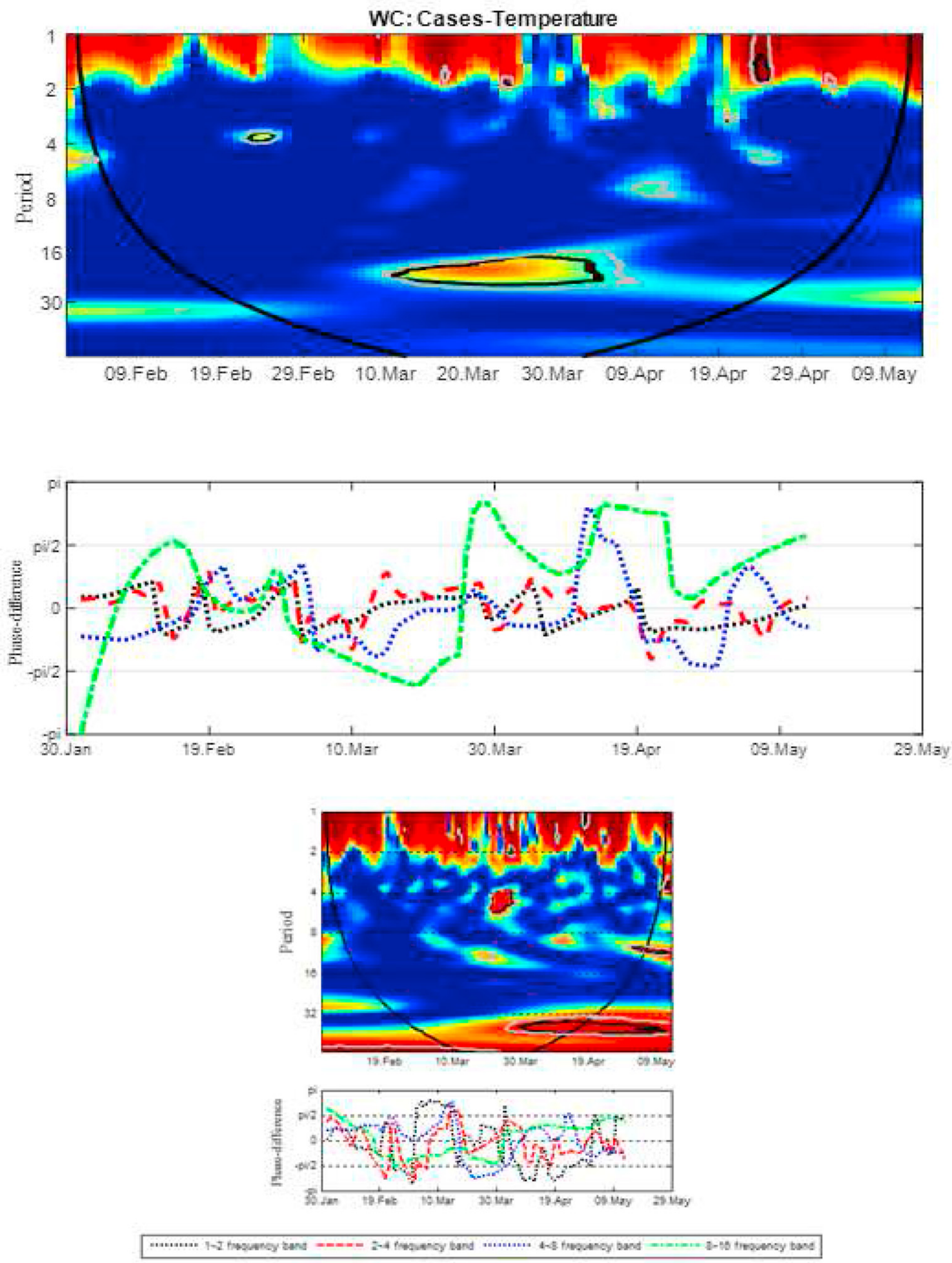
have a long-term impact on the currency exchange markets of the countries under study.

4. Discussion

The wavelet-coherence between the number of confirmed COVID-19 cases and temperature reveals short-term and long-term co-movements between COVID-19 cases and temperature. For the majority of occasions, there is evidence of cyclicality (in-phase) between the variables, and in most countries, the temperature leads the relationship. This implies that temperature has a significant impact on the spread of the COVID-19 disease, which conforms with some other studies, suggesting that a rise in temperature helps to control the COVID-19 spread. For instance (Tobías and Molina, 2020), opine that high temperature may reduce the transmission of the disease (Prata et al., 2020); report its negative linear relationship with the number of confirmed COVID-19 cases in Brazil, and (Guo et al., 2020; Wu et al., 2020) opine that COVID-19 pandemic may be partially suppressed with increased temperature.

The PWC between the number of confirmed COVID-19 cases and stock market returns (SR), after conditioning for exchange rate returns (ERR) and temperature exhibits short-term and long-term co-movements between the confirmed COVID-19 cases and SR. There is evidence of both cyclical and anti-cyclical patterns of coherence between the variables. Furthermore, strong connectedness at low frequencies displays that

(a)



(b)

Figure 16. United States. (a): WC: Cases - Temperature. (b): PWC: Cases-SR| ERR-Temp.

COVID-19 cases have a long-term impact on the stock markets of the countries under study. Hence, our findings emphasize on the negative association between the COVID-19 cases and the stock market indices under reference. This highlights the fact that the investors became more conscious of the long-term impact of the COVID-19 pandemic, were expecting longer worldwide lockdowns in light of the increasing number of confirmed cases, resulting in economic and social losses. The lockdown imposition in all parts of the world led to a significant drop among the stock market indices points. The stock market returns exhibit higher volatility during the sample period, which was triggered by the COVID-19's multiple impacts, including nationwide lockdown, higher unemployment rates, lower consumption levels, migration of workers, restricted demand and supply chains, and the distressed financial markets (Sharma et al., 2020). Stock markets are leading variables in the economy (Harvey, 1989), and the higher volatility and fluctuations on major stock market returns during the pandemic outbreak document the expected continuous downfall in the national and international financial markets.

However, our empirical findings contradict the results by (He et al., 2020), who observe a non-negative, short-term impact of the COVID-19 pandemic on the stock markets of affected countries. Our results support the findings by (Liu et al., 2020a), highlighting the significant adverse impact of the confirmed COVID-19 cases on the stock market returns across all the affected countries and areas. The findings are also in line with results by (Sharif et al., 2020), suggesting the short-term causality between the COVID-19 pandemic and the US stock market is significant

Table 3. Wavelet coherence: Cases – temperature.

Country	Figure	DB	Dates	Lead	Lag	In-phase/Out-phase
Belgium	2(a)	1–2	30th March, 8th April	Temperature	Cases	In-phase
		1–2	25th April and 29th April - 5th May	Cases	Temperature	In-phase
		2–4	6th March, 25th - 30th March, 6th April	Cases	Temperature	In-phase
		2–4	25th - 29th April	Temperature	Cases	In-phase
		4–8	25th - 29th April	Cases	Temperature	In-phase
		4–8	9th - 17th April and 9th May	Temperature	Cases	In-phase
		8–16	12th - 19th February	Cases	Temperature	In-phase
		8–16	18th - 30th March	Cases	Temperature	Out-phase
		8–16	29th April - 5th May	Temperature	Cases	In-phase
Brazil	3(a)	1–2	12th February, 2nd March, 25th March, 12th April, 28th-3rd April and 15th-19th April	Cases	Temperature	In-phase
		2–4	5th March	Temperature	Cases	Out-Phase
		2–4	25th March, 5th April and 15th -19th April	Cases	Temperature	In-phase
		4–8	28th March - 18th April	Cases	Temperature	In-phase
		4–8	29th April - 5th May	Temperature	Cases	Out-Phase
		8–16	9th-19th February	Temperature	Cases	Out-Phase
		8–16	17th -23rd March and 25th April - 13th May	Cases	Temperature	In-phase
Canada	4(a)	1–2	1st February	Cases	Temperature	In-phase
		1–2	29th February and 10th March	Cases	Temperature	Out-phase
		1–2	18th April, 23rd April and 1st May	Temperature	Cases	Out-phase
		2–4	25th March	Cases	Temperature	In-phase
		4–8	5th April	Temperature	Cases	In-phase
		2-4 & 4-8	1st - 9th May	Temperature	Cases	In-phase
		4–8	7th - 23rd April	Cases	Temperature	In-phase
		8–16	18th March - 28th March	Cases	Temperature	In-phase
		8–16	28th March - 3rd April	Temperature	Cases	In-phase
		8–16	9th April - 3rd May	Cases	Temperature	Out-phase
China	5(a)	1–2	25th February and 15th April	Cases	Temperature	In-phase
		1–2	5th May	Temperature	Cases	In-phase
		2–4	2nd April and 16th April	Cases	Temperature	In-phase
		4–8	22nd - 30th March	Temperature	Cases	Out-Phase
		2-4 & 4-8	9th - 19th February	Temperature	Cases	In-phase
		8–16	12th - 22nd February and 17th - 27th February	Cases	Temperature	Out-phase
France	6(a)	1–2	11th February, 19th February and 20th March	Temperature	Cases	In-phase
		1–2	7th April, 15th - 17th April, 1st May and 9th May	Cases	Temperature	In-phase
		2–4	25th March - 5th April	Temperature	Cases	In-phase
		2–4	9th - 19th April	Cases	Temperature	In-phase
		4–8	25th March - 25th April and 5th - 9th May	Cases	Temperature	In-phase
		8–16	15th February	Cases	Temperature	In-phase
		8–16	5th - 9th April	Cases	Temperature	Out-Phase
Germany	7(a)	1–2	1st February, 5th March, 18th March - 8th April, 19th April and 27th April	Cases	Temperature	In-phase
		2–4	5th - 10th March & 15th April	Temperature	Cases	In-phase
		2–4	30th March, 1st May and 9th May	Cases	Temperature	In-phase
		4–8	30th March	Temperature	Cases	In-phase

(*continued on next page*)

Table 3 (*continued*)

Country	Figure	DB	Dates	Lead	Lag	In-phase/Out-phase
		4–8	9th May	Cases	Temperature	In-phase
		8–16	10th - 20th March	Cases	Temperature	Out-Phase
		8–16	7th - 20th April	Temperature	Cases	In-phase
India	8(a)	1–2	5th - 17th April and 11th May	Cases	Temperature	In-phase
		2–4	5th March, 22nd March and 15th April	Temperature	Cases	In-phase
		1-2 & 2-4	5th February and 15th March	Cases	Temperature	In-phase
		4–8	9th February and 27th February - 5th March	Temperature	Cases	In-phase
		2-4 & 4-8	25th March	Temperature	Cases	Out-Phase
		8–16	12th - 19th February	Temperature	Cases	In-phase
Iran	9(a)	1–2	3rd - 7th February and 29th April	Temperature	Cases	In-phase
		1–2	24th - 25th March and 3rd -5th April	Cases	Temperature	In-phase
		2–4	2nd - 8th April	Cases	Temperature	In-phase
		2–4	22nd - 27th April	Temperature	Cases	In-phase
		4–8	11th - 13th March and 19th - 27th April	Temperature	Cases	In-phase
		8–16	8th - 13th March	Cases	Temperature	In-phase
		8–16	28th March - 9th April	Temperature	Cases	In-phase
Italy	10(a)	1–2	6th - 7th February, 28th February - 3rd March, 14th - 20th, 23rd - 26th March and 31st March - 4th April	Temperature	Cases	In-Phase
		2–4	28th - 29th February and 30th April - 2nd May	Temperature	Cases	In-Phase
		2–4	14th - 18th March, 22nd - 28th March and 21st - 22nd April	Cases	Temperature	In-Phase
		4–8	12th - 31st March and 11th - 19th April	Cases	Temperature	In-Phase
		4–8	1st - 11th April and 6th - 9th May	Temperature	Cases	In-Phase
		8–16	16th - 22nd April	Cases	Temperature	Out-Phase
Peru	11(a)	1–2	18th - 21st March	Cases	Temperature	In-Phase
		1–2	31st March - 3rd April, 8th, 16th and 17th April	Temperature	Cases	In-Phase
		2–4	25th March and 6th - 7th April	Temperature	Cases	In-Phase
		4–8	12th - 20th April and 23rd - 29th April	Cases	Temperature	In-Phase
		8–16	4th - 19th April	Cases	Temperature	In-Phase
Russia	12(a)	1–2	26th - 28th February, 22nd - 24th March and 30th March - 3rd April	Temperature	Cases	In-Phase
		1–2	25th - 28th April and 11th - 14th May	Cases	Temperature	In-Phase
		2–4	10th March, 22nd March and 11th April	Temperature	Cases	In-Phase
		2–4	28th April and 1st May	Cases	Temperature	In-Phase
		4–8	6th -12th March and 30th March -8th April	Temperature	Cases	In-Phase
		4–8	22nd April - 9th May	Cases	Temperature	In-Phase
		8–16	12th - 18th February	Temperature	Cases	Out-Phase
		8–16	22nd April - 8th May	Cases	Temperature	In-Phase
Spain	13(a)	1–2	14th - 17th March and 23rd - 28th April	Temperature	Cases	In-Phase
		1–2	29th - 30th March and 9th - 10th May	Cases	Temperature	In-Phase
		2–4	15th - 18th March	Temperature	Cases	In-Phase
		2–4	30th March - 9th April	Cases	Temperature	In-Phase
		4–8	11th - 14th March, 8th - 30th March, 2nd - 6th April, 23rd - 30th April and 1st - 2nd May	Temperature	Cases	In-Phase
		4–8	31st March - 2nd April	Cases	Temperature	In-Phase
Turkey	14(a)	1–2	21st February, 12th March and 5th - 11th May	Temperature	Cases	In-phase
		1–2	5th April, 20th April and 25th April	Cases	Temperature	In-phase
		1-2 & 2-4	5th March	Temperature	Cases	In-phase

(*continued on next page*)

Table 3 (*continued*)

Country	Figure	DB	Dates	Lead	Lag	In-phase/Out-phase
		2–4	2nd April	Cases	Temperature	In-phase
		2–4	1st May	Temperature	Cases	In-phase
		2-4 & 4-8	20th - 30th March	Temperature	Cases	In-phase
		4–8	15th April	Temperature	Cases	Out-Phase
		8–16	19th April	Cases	Temperature	Out-Phase
United Kingdom	15(a)	1–2	1st March	Cases	Temperature	In-phase
		1–2	25th March, 29th March, 7th April and 13th April	Temperature	Cases	In-phase
		2–4	15th - 27th March	Temperature	Cases	In-phase
		2-4 & 4-8	30th March - 15th April	Temperature	Cases	In-phase
		4–8	29th April - 11th May	Cases	Temperature	In-phase
United States	16(a)	1–2	9th March, 25th April and 2nd May	Temperature	Cases	In-phase
		1–2	17th March and 25th March	Cases	Temperature	In-phase
		2–4	25th February and 5th April	Cases	Temperature	In-phase
		2–4	20th April	Temperature	Cases	In-phase
		4–8	9th April - 25th April	Temperature	Cases	In-phase

Note: DB represents Day bands.

at all frequencies analyzed. Expansionary policies by the US Federal Reserve and government led to a 37% increase in its stock prices from the end of March 2020 (Thorbecke, 2020). Furthermore (Zhang et al., 2020), opine that the individual stock market reactions are clearly linked to the severity of the outbreak in each country across the globe and the greater uncertainty has caused the markets to become highly volatile and unpredictable. Between March 6th and 18th, 2020, all major stock market indices lost value due to the COVID-19 pandemic sweeping across the globe. The CSI 300 index in China lost 12.1 percent of its value during this period, whereas the FTSE MIB index in Italy lost 27.3 percent of its value (Statista, 2020). Global stock markets have reflected the investor sentiments, crashing to historic lows since the Global Financial Crisis of 2008 (Ravi, 2020). UNCTAD (2020) projects global depression with the varied potential impact of the COVID-19 shock on the global economy, due to sudden halt of economies activities, resulting in loss of income and large-scale unemployment, along with the adverse effects on the financial markets, investment confidence, international trade and commodity prices.

The PWC between the number of confirmed COVID-19 cases and exchange rate return (ERR), after conditioning for stock market returns (SR) and temperature indicates that COVID-19 cases and ERR correlate or move together mostly in the short-and long-term over the sample period. There is evidence of both cyclicality and anti-cyclicality between the variables. Due to the pandemic outbreak, the currency market has witnessed a change in the price of the money. Since January 2020, the Euro exchange rate has been unstable, and the currency revival rests on how swiftly the economy resurges from this pandemic (Chronicle Live, 2020). Additionally, the majority of the countries under study report COVID-19 cases to be leading, which implies a significant impact of the pandemic outbreak on the currency exchange market of these countries. Furthermore, strong connectedness at low frequencies display that COVID-19 cases have a long-term impact on the currency exchange markets of the countries under study. This implies that the rise in the number of COVID-19 cases has a significant effect on the fluctuations and volatility of these countries' currency exchange rates. Alternatively, UNCTAD (2020) projects the developing countries as a whole (excluding China) to lose nearly $800 billion in terms of export revenue in 2020. Hence, the foreign exchange earnings will increase the challenges already imposed by currency depreciations with respect to the US dollar.

Regarding Chinese currency, our findings highlight the presence of a significant (in-the-phase) co-movement between the ERR and COVID-19 cases, contradicting (Iqbal et al., 2020), where the authors report a significant negative (out-of-phase) coherence between the exchange rate and COVID-19 cases, suggesting a little impact of the COVID-19 cases on the Chinese exports. Alternatively (Gunay, 2020), examines foreign exchange markets including USD/GBP, USD/TRY and USD/BRL and their reaction to the pandemic, concluding that the tensions depicted through the media regarding the spread of the pandemic is less incorporated in the exchange markets as of April, 2020. However, our results have further elaborated on the impact, suggesting that the continuous increase in the number of COVID-19 cases in these countries has a significant impact on the fluctuations and variability of their exchange markets. Furthermore, examining the dynamics of the COVID-19 variables and the exchange rate movements in emerging markets currencies, including Brazilian Real (BRL) and Russian Ruble (RBL) (Villarreal-Samaniego, 2020), reports that in such crisis of the COVID-19 pandemic and steep oil price declines, have led to currencies depreciation. The currency depreciation of all major emerging countries (BRL, RUB, TRY) accelerated in February–March 2020 with the imposition of lockdowns, and over this period, the currencies of advanced economies (USD, Euro, Japanese Yen) strengthened (OECD, 2020). The Canadian and Australian dollar rebounded after a notable decline in the first half of March (Balji, 2020). With respect to Europe, the countries severely affected by the disease, particularly Italy and Spain, are exhibiting the worst economic effects, with their currencies free falling with less investment in their systems (Chronicle Live, 2020). While our findings highlight on a significant

Table 4. Partial wavelet coherence (PWC): Cases-SR| ERR-Temperature.

Country	Figure	DB	Dates	Lead	Lag	In-phase/Out-phase
Belgium	2(b)	1–2	5th April	Cases	SR	Out-phase
		2–4	20th March - 10 April	SR	Cases	Out-phase
		4–8	25th February, 15th April and 3rd May	SR	Cases	In-phase
		8–16	15th - 19th April and 20th April - 10th May	SR	Cases	In-phase
Brazil	3(b)	1–2	10th February	SR	Cases	Out-phase
		1–2	19th February - 10th March	Cases	SR	Out-phase
		1–2	28th March - 3rd April	SR	Cases	Out-Phase & In-phase
		1–2	5th May	SR	Cases	In-phase
		1-2 & 2–4	15th April	Cases	SR	In-phase
		2–4	25th February	Cases	SR	Out-phase
		2-4 & 4–8	30th March	SR	Cases	In-phase
		4–8	25th April	SR	Cases	In-phase
		4–8	10th - 19th April	Cases	SR	In-phase
		8–16	19th-25th April	Cases	SR	In-phase
Canada	4(b)	1–2	10th -19th February and 30th April	SR	Cases	Out-phase
		1–2	30th March	SR	Cases	In-phase
		2–4	29th February	SR	Cases	In-phase
		4–8	15th March - 10th April	SR	Cases	Out-phase
		8–16	9th February and 12 March	Cases	SR	In-phase
China	5(b)	1–2	25th March	SR	Cases	In-phase
		1–2	5th April and 15th - 25th April	Cases	SR	Out-phase
		2–4	9th February	Cases	SR	In-phase
		2–4	29th February	SR	Cases	Out-phase
		4–8	9th February and 9th May	Cases	SR	In-phase
		8–16	1st May	SR	Cases	In-phase
France	6(b)	1–2	19th February, 1st - 10th March and 28th March	SR	Cases	Out-phase
		1–2	18th March, 18th - 22nd April and 9th - 13 May	Cases	SR	Out-phase
		2–4	15th February, 29th February, 9th March and 1st April	Cases	SR	In-phase
		2–4	9th May	SR	Cases	In-phase
		4–8	5th March and 12th March	SR	Cases	In-phase
		4–8	19th April	SR	Cases	Out-phase
		4–8	28th April	Cases	SR	In-phase
		8–16	25th - 30th April	SR	Cases	In-phase
Germany	7(b)	1–2	5th February and 19th February	SR	Cases	Out-phase
		1–2	12th March and 8th May	Cases	SR	Out-phase
		1–2	26th March	Cases	SR	In-phase
		1-2 & 2–4	10th April and 19th - 25th April	Cases	SR	Out-phase
		2–4	15th February	Cases	SR	In-phase
		2–4	12th March and 20th - 30th March	SR	Cases	In-phase
		4–8	5th May, 20th - 30th March and 28th April	SR	Cases	In-phase
		4–8	27th February and 5th - 9th April	Cases	SR	Out-phase

(continued on next page)

Table 4 (*continued*)

Country	Figure	DB	Dates	Lead	Lag	In-phase/Out-phase
		4–8	15th March	Cases	SR	In-phase
		8–16	20th - 25th March	Cases	SR	In-phase
India	8(b)	1–2	9th February, 20th February	SR	Cases	Out-phase
		1–2	12th March	Cases	SR	Out-phase
		1–2	27th February, 28th March - 2nd April	SR	Cases	In-phase
		2–4	8th March, 30th March and 5th - 9th May	SR	Cases	In-phase
		1-2 & 2–4	10th April	Cases	SR	Out-phase
		1-2 & 2–4	19th April	Cases	SR	In-phase
		4–8	5th March, 25th - 30th March	Cases	SR	In-phase
		4–8	15th - 20th March	SR	Cases	Out-phase
		4–8	18th April	SR	Cases	In-phase
		8–16	19th - 29th February	Cases	SR	In-phase
		8–16	25th - 30th March and 15th April - 5th May	Cases	SR	Out-phase
Iran	9(b)	1–2	7th - 9th February and 5th May	Cases	SR	In-Phase
		1–2	16th March and 24th - 26th March	SR	Cases	In-phase
		2–4	3rd - 6th March	Cases	SR	In-Phase
		2–4	25th - 26th April	Cases	SR	Out-Phase
		4–8	2nd - 5th March	Cases	SR	In-Phase
		4–8	20th - 22nd March	SR	Cases	In-Phase
		4–8	26th March - 3rd April	SR	Cases	Out-Phase
		8–16	27th - 30th March	Cases	SR	In-Phase
		8–16	10th - 12th April and 2nd - 5th May	SR	Cases	In-phase
Italy	10(b)	1–2	23rd - 26th February	SR	Cases	In-Phase
		1–2	8th - 10th March	Cases	SR	Out-Phase
		1–2	27th March	SR	Cases	Out-Phase
		1–2	29th April	Cases	SR	In-Phase
		2–4	9th - 10th February, 20th - 21st and 24th - 29th April	Cases	SR	In-Phase
		2–4	7th - 10th and 12th -15th March	Cases	SR	Out-Phase
		4–8	5th - 9th March and 21st - 24th April	SR	Cases	In-Phase
		4–8	29th - 31st March	Cases	SR	Out-Phase
		8–16	20th - 26th March	Cases	SR	In-Phase
Peru	11(b)	1–2	17th February	SR	Cases	Out-Phase
		1–2	19th - 22nd April and 7th May	Cases	SR	Out-Phase
		2–4	22nd March,	SR	Cases	In-Phase
		2–4	26th - 31st March	Cases	SR	Out-Phase
		2–4	9th – 12th May	SR	Cases	Out-Phase
		4–8	29th February - 1st March	SR	Cases	In-Phase
		8–16	22nd April - 7th May	Cases	SR	In-Phase
Russia	12(b)	1–2	2nd - 8th February, 23rd February, 1st - 2nd March and 20th - 21st April	Cases	SR	In-Phase
		1–2	26th - 27th March	Cases	SR	Out-Phase
		2–4	20th March and 10th - 11th April	SR	Cases	In-Phase
		2–4	22nd - 25th April and 6th - 9th May	Cases	SR	In-Phase

(*continued on next page*)

Table 4 (*continued*)

Country	Figure	DB	Dates	Lead	Lag	In-phase/Out-phase
		4–8	6th - 10th March	Cases	SR	Out-Phase
		4–8	20th - 28th March and 27th - 29th April	SR	Cases	In-Phase
		8–16	1st - 14th April	SR	Cases	In-Phase
Spain	13(b)	1–2	5th - 8th February	SR	Cases	Out-Phase
		1–2	18th - 20th February, 1st March, 8th March, 20th - 30th March, 1st - 6th April, 11th April and 19th April	Cases	SR	In-Phase
		2–4	21st -3rd March and 29th April	Cases	SR	In-Phase
		2–4	6th May	SR	Cases	In-Phase
		4–8	25th - 27th March	SR	Cases	Out-Phase
		4–8	8th - 9th April	Cases	SR	Out-Phase
		4-8 & 8-16	20th - 28th March	SR	Cases	In-Phase
Turkey	14(b)	1–2	19th February	SR	Cases	Out-phase
		1–2	27th February - 5th March, 20th March and 15th April	Cases	SR	Out-phase
		1–2	28th March and 25th April	SR	Cases	In-phase
		1-2 & 2–4	27th February	Cases	SR	Out-phase
		2–4	10th April and 25th April	SR	Cases	In-phase
		2–4	19th April and 2nd May	Cases	SR	In-phase
		4–8	12th March - 2nd April	Cases	SR	Out-phase
		4–8	19th April	SR	Cases	In-phase
		8–16	5th - 15th March	SR	Cases	In-phase
		8–16	19th April - 1st May	Cases	SR	In-phase
United Kingdom	15(b)	1–2	9th March, 28th March, 5th April, 10th April, 1st May and 9th May	SR	Cases	In-phase
		1–2	10th February and 20th March	Cases	SR	In-phase
		2–4	25th February	Cases	SR	In-phase
		2–4	12th March, 30th March - 10th April and 30th April - 5th May	SR	Cases	In-phase
		2-4 & 4–8	10th - 12th March	SR	Cases	In-phase
		2–4	20th March	Cases	SR	In-phase
		4–8	15th - 30th March, 5th May	Cases	SR	Out-phase
		4–8	26th February	SR	Cases	In-phase
		4–8	12th April	SR	Cases	Out-phase
		8–16	9th February	Cases	SR	Out-phase
		8–16	19th April	SR	Cases	Out-phase
United States	16(b)	1–2	25th February, 11th April and 19th April	Cases	SR	Out-phase
		1–2	11th March	SR	Cases	Out-phase
		1-2 & 2–4	28th March	Cases	SR	In-phase
		2–4	20th - 30th March	SR	Cases	In-phase
		4–8	20th - 30th March	Cases	SR	Out-phase
		8–16	20th March	SR	Cases	In-phase
		8–16	10th April and 5th May	Cases	SR	In-phase

Note: DB represents Day Bands.

Table 5. Partial wavelet coherence (PWC): Cases-ERR| SR-Temperature.

Country	Figure	DB	Dates	Lead	Lag	In-phase/Out-phase
Belgium	2(c)	1–2	8th - 19th Feb	Cases	ERR	Out-phase
		2–4	18th -25th Feb	ERR	Cases	In-phase
		2–4	1st - 5th April and 5th – 9th May	Cases	ERR	Out-phase
		4–8	19th - 23rd April	Cases	ERR	Out-phase
		8–16	5th - 23rd March	Cases	ERR	Out-phase
Brazil	3(c)	1–2	19th February and 10th March	Cases	ERR	In-phase
		1–2	30th March	ERR	Cases	Out-phase
		1–2	5th - 9th May	Cases	ERR	Out-phase
		1-2 & 2-4	10th-15th April	Cases	ERR	In-phase
		2–4	15th March	Cases	ERR	Out-phase
		2–4	28th March	ERR	Cases	Out-phase
		2–4	5th May	Cases	ERR	In-phase
		4–8	15th April	Cases	ERR	In-phase
		8–16	17th-29th April	ERR	Cases	Out-phase
Canada	4(c)	1-2 & 2-4	15th February	ERR	Cases	In-phase
		1–2	25th February and 30th March	Cases	ERR	Out-phase
		1–2	29th April - 9th May	ERR	Cases	In-phase
		2–4	25th March and 19th April	Cases	ERR	In-Phase & Out-phase
		2–4	1st - 9th May	ERR	Cases	In-phase
		4–8	5th May, 25th March and 5th April	ERR	Cases	In-phase
		8–16	19th April - 13th May	Cases	ERR	In-phase
China	5(c)	1–2	15th - 17th February, 7th April, 15th April and 30th April	Cases	ERR	In-Phase
		1–2	17th - 19th February and 15th March	ERR	Cases	Out-phase
		1-2 & 2-4	19th April	ERR	Cases	Out-phase
		2–4	15th - 17th February	ERR	Cases	In-phase
		2–4	17th - 19th February	Cases	ERR	In-phase
		2–4	15th March	Cases	ERR	Out-phase
		2–4	10th March and 9th May	Cases	ERR	Out-phase
		2–4	25th April	ERR	Cases	In-phase
		2-4 & 4-8	20th March	Cases	ERR	In-phase
		4–8	9 February and 9th May	ERR	Cases	In-phase
		4-8 & 8-16	19th February	Cases	ERR	In-phase
France	6(c)	1–2	19th February, 25th February and 15th March	ERR	Cases	In-phase
		1–2	8th March, 20th March, 28th March and 9th April	Cases	ERR	Out-phase
		1–2	9th - 13th May	Cases	ERR	In-phase
		2–4	15th February, 15th March and 9th April	ERR	Cases	In-phase
		2–4	30th March	ERR	Cases	Out-phase
		2–4	29th April - 12th May	Cases	ERR	In-phase
		4–8	5th March	Cases	ERR	In-phase
		4–8	29th April - 13th May and 9th May	ERR	Cases	Out-phase
		4–8	30th March - 9th April	ERR	Cases	In-phase
		8–16	10th - 20th March and 30th March - 9th April	ERR	Cases	In-phase
		8–16	22nd - 29th April	Cases	ERR	In-phase

(continued on next page)

Table 5 (*continued*)

Country	Figure	DB	Dates	Lead	Lag	In-phase/Out-phase
Germany	7(c)	1–2	5 February, 9th February, 19th February, 12th March and 28th March	ERR	Cases	In-phase
		1–2	18th April - 5th May	Cases	ERR	Out-phase
		1-2 & 2-4	10th April	Cases	ERR	In-phase
		2–4	15th February and 25th February,	ERR	Cases	In-phase
		2–4	5th March, 12th March and 20th -25th March	Cases	ERR	In-phase
		2–4	25th April - 2nd May	Cases	ERR	Out-phase
		4–8	5th Feb	ERR	Cases	In-phase
		4–8	10th - 30th March	ERR	Cases	Out-phase
		4–8	28th April - 2nd May	Cases	ERR	In-phase
		8–16	10th - 30th March	Cases	ERR	In-phase
India	8(c)	1–2	9th -22nd February, 1st - 3rd March and 17th April	ERR	Cases	Out-phase
		1–2	28th March	ERR	Cases	In-phase
		1–2	10th April	Cases	ERR	In-phase
		1-2 & 2-4	30th March - 5th April,	Cases	ERR	In-phase
		2–4	3rd March	ERR	Cases	Out-phase
		2–4	22nd April, 1st May and 9th May	ERR	Cases	In-phase
		4–8	29th February - 5th March, 20th - 30th March and 17th April	Cases	ERR	In-phase
		8–16	9th - 19th February, 25th - 29th February, 10th March, 20th - 30th March and 15th April - 5th May	Cases	ERR	In-phase
Iran	9(c)	1–2	1st March	ERR	Cases	In-phase
		1–2	4th - 5th May	ERR	Cases	Out-Phase
		2–4	20th - 22nd February, 2nd April and 30th April - 2nd May	ERR	Cases	In-phase
		2–4	10th April and 15th - 16th April	ERR	Cases	Out-Phase
		4–8	25th - 31st March and 30th March - 5th April	ERR	Cases	In-phase
		4–8	26th April - 1st May	Cases	ERR	In-Phase
		8–16	12th March - 18th April	Cases	ERR	In-Phase
		8–16	29th April - 1st May	ERR	Cases	In-phase
Italy	10(c)	1–2	10th - 17th February, 20th - 21st February, 20th March and 9th - 10th May	ERR	Cases	In-Phase
		1–2	14th March, 28th March and 11th April	Cases	ERR	Out-Phase
		2–4	7th - 11th February, 5th March and 8th -11th April	Cases	ERR	In-Phase
		2–4	16th - 17th March and 28th - 29th April	ERR	Cases	In-Phase
		2–4	30th - 31st March	Cases	ERR	Out-Phase
		4–8	3rd - 22nd March and 22nd April	ERR	Cases	Out-Phase
		8–16	16th - 26th March	ERR	Cases	Out-Phase
Peru	11(c)	1–2	14th - 15th February and 22nd - 30th March	ERR	Cases	Out-Phase
		1–2	24th - 26th February	Cases	ERR	In-Phase
		1–2	22nd April	ERR	Cases	In-Phase
		2–4	25th - 31st March	ERR	Cases	In-Phase
		2–4	18th - 22nd March	Cases	ERR	Out-Phase
		4–8	12th - 22nd March	Cases	ERR	Out-Phase
		4–8	8th – 10th April, 22nd - 29th April	Cases	ERR	In-Phase
		8–16	20th - 23rd March	ERR	Cases	In-Phase
Russia	12(c)	1–2	4th - 8th February, 20th - 21st April	Cases	ERR	In-Phase
		1–2	2nd -4th March	ERR	Cases	Out-Phase
		1–2	20th March, 26th - 28th March	Cases	ERR	Out-Phase

(*continued on next page*)

Table 5 (*continued*)

Country	Figure	DB	Dates	Lead	Lag	In-phase/Out-phase
		2–4	29th February - 2nd March, 9th -12th March, 4th - 10th April	Cases	ERR	Out-Phase
		2–4	20th - 24th March	ERR	Cases	In-Phase
		2–4	19th April, 7th - 8th May	Cases	ERR	In-Phase
		2–4	20th March	ERR	Cases	Out-Phase
		4–8	3rd - 10th April	Cases	ERR	Out-Phase
		4–8	11th - 18th April	ERR	Cases	In-Phase
		8–16	7th - 8th May	Cases	ERR	In-Phase
Spain	13(c)	1–2	3rd February	ERR	Cases	Out-Phase
		1–2	14th - 21st February and 6th and 9th April	ERR	Cases	In-Phase
		1–2	27th February - 2nd March	Cases	ERR	Out-Phase
		2–4	13th - 20th February, 26th - 29th February, 28th March, 4th April and 18th April	ERR	Cases	In-Phase
		2–4	18th - 23rd March	ERR	Cases	Out-Phase
		4–8	18th - 19th March, 25th - 26th March and 7th - 10th April	Cases	ERR	In-Phase
		4–8	17th - 18th April	ERR	Cases	In-Phase
		8–16	7th - 13th March	Cases	ERR	Out-Phase
		8–16	21st - 31st March	Cases	ERR	In-Phase
		8–16	13th -18th March	ERR	Cases	In-Phase
Turkey	14(c)	1–2	9th February, 19th February, 22nd February, 29th April and 2nd May	Cases	ERR	Out-phase
		1–2	2nd March	ERR	Cases	Out-phase
		1–2	17th April	Cases	ERR	In-phase
		2–4	7th February, 17th February and 30th March	ERR	Cases	In-phase
		2–4	29th February and 10th April	Cases	ERR	In-phase
		4–8	9th February and 9th May	ERR	Cases	Out-phase
		4–8	19th April	ERR	Cases	In-phase
		8–16	29th February -20th March	ERR	Cases	In-phase
		8–16	19th April - 5th May	Cases	ERR	In-phase
United Kingdom	15(c)	1–2	9th - 15th February, 25th February, 29th February - 10th March, 18th March, 21st March, 5th April, 17th April	Cases	ERR	In-phase
		1-2 & 2-4	30th March	Cases	ERR	In-phase
		2–4	10th February, 15th February, 25th February, 15th March and 20th April	Cases	ERR	In-phase
		2–4	29th February	ERR	Cases	In-phase
		4–8	9th February, 10th - 30th March	ERR	Cases	Out-phase
		4–8	9th April	ERR	Cases	In-phase
		4–8	8th May	Cases	ERR	In-phase
		8–16	1st-9th April	ERR	Cases	In-phase

Note: DB represents Day Bands.

relationship between the increase in the COVID-19 cases and Indian currency (INR) (Livemint, 2020b), reports rupee to slide the record low of 76. 92 against the US dollar. Additionally, the analyzts do not anticipate any strengthening of the rupee, until the COVID-19 curve flattens (Livemint, 2020a). Furthermore, by March 20, the US infections began to spur, inducing many US citizens to withdraw cash from the banks due to rising uncertainty and limitations on movements that weakened the consumption level, leading to an appreciation in the dollar to the Yen (World Economic Forum, 2020).

5. Conclusions

We employed the wavelet coherence and the partial wavelet coherence to examine the nexus between the number of confirmed COVID-19 cases, temperature, exchange rates and stock market returns in the top-15 most affected countries. The wavelet-based approach enables us to identify the lead-lag interactions in the time-frequency domain and overcome some inherent challenges, including stationarity and non-linearity. This study adds to the literature, as it implements the wavelet coherence technique to explore the unexpected outbreak effects of the global pandemic on the temperature, currency exchange rates and stock market returns, collectively.

The current research is one of the pioneer studies on the economic effects of the COVID-19 pandemic, and the importance of research in this area is further highlighted by Goodell (2020) and Villarreal-Samaniego (2020). Our results state that (i) there is evidence of cyclicality between temperature and COVID-19 cases, implying that average daily temperature has a significant impact on the spread of the COVID-19 disease in most of the countries; (ii) strong connectedness at low frequencies display that COVID-19 cases have a significant long-term impact on the exchange rate returns and stock markets returns of the most affected countries under study; (iii) after controlling for the effect of stock market returns and temperature, the co-movements between the confirmed COVID-19 cases and exchange rate returns becomes stronger; (iv) after controlling for the effect of exchange rate returns and temperature, the co-movements between the confirmed COVID-19 cases and stock market returns becomes stronger.

Our findings offer significant and fresh policy and practical implications. The economic and financial costs of the COVID-19 pandemic concern the society, policymakers, financial institution experts and individual investors. From an investment perspective, our results exhibit the long-lasting and significant impact of COVID-19 cases on the stock market returns and exchange rate returns, and hence, the portfolio managers investors must prepare their portfolios to handle the volatility and systematic risk associated with COVID-19 spread. By observing the time-frequency relationship between COVID-19 outbreak, oil price, geopolitical risk, economic uncertainty and US stock market, Sharif et al. (2020) emphasize the uncertainties from the pandemic outbreak to be the primary source of concern for the US policymakers. Extreme coordination and cooperation at the national and global level is required for the world organisations, world banks, central banks, and government officials to tackle this challenge, especially to tackle international trade, exports and economic sectors like travel, tourism, and hospitality.

Since this paper presents an initial analysis of the pandemic issue, there is significant scope for future research. Data on temperature is collected for each country's capital that might not precisely reflect the nation's climate trends. Future research shall overcome this limitation. We notice strong co-movements, and hence factors explaining such co-movements can be identified. Accordingly, future research may consider the short and long-run effect of the novel COVID-19 pandemic on the other variables such as GDP growth rate, Production Price Index, employment rate, monetary policy and other such macro-economic variables along with considering larger data samples.

Declarations

Author contribution statement

A.K. Tiwari: Conceived and designed the experiments; Performed the experiments; Analyzed and interpreted the data; Wrote the paper.

G.D. Sharma: Conceived and designed the experiments; Performed the experiments; Wrote the paper.

M. Jain, A. Yadav and B. Erkut: Analyzed and interpreted the data; Contributed reagents, materials, analysis tools or data; Wrote the paper.

Funding statement

This research did not receive any specific grant from funding agencies in the public, commercial, or not-for-profit sectors.

Declaration of interests statement

The authors declare no conflict of interest.

Data availability statement

The authors do not have permission to share data.

Additional information

Supplementary content related to this article has been published online at https://doi.org/10.1016/j.heliyon.2021.e06181.

Acknowledgements

We would like to show our gratitude to our universities for giving us the platform, time, and infrastructure to conduct our research work smoothly. We also thank annoynomus referees for their valuable comments which helped us to improve paper considerably.

References

Afshan, S., Sharif, A., Loganathan, N., Jammazi, R., 2018. Time–frequency causality between stock prices and exchange rates: further evidences from cointegration and wavelet analysis. Phys. Stat. Mech. Appl. 495, 225–244.
Aguiar-Conraria, L., Soares, M.J., 2011. Oil and the macroeconomy: using wavelets to analyze old issues. Empir. Econ. 40 (3), 645–655.
Aguiar-Conraria, L., Azevedo, N., Soares, M.J., 2008. Using wavelets to decompose the time-frequency effects of monetary policy. Phys. Stat. Mech. Appl. 387 (12), 2863–2878.
Aloui, D., Goutte, S., Guesmi, K., Hchaichi, R., 2020. COVID 19's impact on crude oil and natural gas S&P GS indexes. SSRN Electron. J.
Auler, A.C., Cássaro, F.A.M., da Silva, V.O., Pires, L.F., 2020. Evidence that high temperatures and intermediate relative humidity might favor the spread of COVID-19 in tropical climate: a case study for the most affected Brazilian cities. Sci. Total Environ. 729, 139090.
Balji, D., 2020. Catalysts that Could Make or Break the Canadian Dollar's Rebound. Bloomberg Quint. Retrieved from. https://www.bloombergquint.com/markets/catalysts-that-could-make-or-break-the-canadian-dollar-s-rebound.
Bedford, T., Riley, S., Barr, I.G., Broor, S., Chadha, M., Cox, N.J., Russell, C.A., 2015. Global circulation patterns of seasonal influenza viruses vary with antigenic drift. Nature 523 (7559), 217–220.
Benhmad, F., 2012. Modeling nonlinear Granger causality between the oil price and U.S. dollar: a wavelet based approach. Econ. Modell. 29 (4), 1505–1514.
Bouoiyour, J., Selmi, R., Tiwari, A.K., Shahbaz, M., 2015. The nexus between oil price and Russia's real exchange rate: better paths via unconditional vs conditional analysis. Energy Econ. 51, 54–66.
Chang, C.-L., McAleer, M., Wong, W.-K., 2020. Risk and financial management of COVID-19 in business, economics and finance. J. Risk Financ. Manag. 13 (5), 102.

Chronicle Live, 2020. The Pound to Euro Exchange War and the Impact of Covid-19 on Forex Markets. Retrieved June 4, 2020, from. https://www.chroniclelive.co.uk/special-features/pound-euro-exchange-war-impact-18217292.
CNA, 2020. Novel Coronavirus COVID-19 - Latest News | CNA. Retrieved June 30, 2020, from Channel News Asia website: https://www.channelnewsasia.com/news/topics/coronavirus-covid-19.
Conlon, T., McGee, R., 2020. Safe haven or risky hazard? Bitcoin during the Covid-19 bear market. Finance Res. Lett. 35, 101607.
Conlon, T., Corbet, S., McGee, R.J., 2020. Are cryptocurrencies a safe haven for equity markets? An international perspective from the COVID-19 pandemic. Res. Int. Bus. Finance 54, 101248.
Deccan Herald, 2020. Covid-19 spread may spike in monsoon, winter with fall in temperatures: IIT-AIIMS study. Retrieved from. https://www.deccanherald.com/science-and-environment/covid-19-spread-may-spike-in-monsoon-winter-with-fall-in-temperatures-iit-aiims-study-863141.html.
Fareed, Z., Iqbal, N., Shahzad, F., Shah, S.G.M., Zulfiqar, B., Shahzad, K., Shahzad, U., 2020. Co-variance nexus between COVID-19 mortality, humidity, and air quality index in Wuhan, China: new insights from partial and multiple wavelet coherence. Air Quality, Atmosphere and Health 13, 673–682.
Github, 2020. Novel Coronavirus (COVID-19) Cases Data. Retrieved May 12, 2020, from John Hopkins website. https://data.humdata.org/dataset/novel-coronavirus-2019-ncov-cases.
Goodell, J.W., 2020. COVID-19 and finance: agendas for future research. Finance Res. Lett. 35 (101512).
Goodell, J.W., Goutte, S., 2020. Co-movement of COVID-19 and Bitcoin: evidence from wavelet coherence analysis. Finance Res. Lett.
Gunay, S., 2020. COVID-19 pandemic versus global financial crisis: evidence from currency market. SSRN Electron. J.
Guo, X.-J., Zhang, H., Zeng, Y., 2020. Transmissibility of COVID-19 and its Association with Temperature and Humidity, pp. 1–12. Https://Www.Researchsquare.Com/Article/Rs-17715/V1.
Harvey, C.R., 1989. Forecasts of economic growth from the bond and stock markets. Financ. Anal. J. 45 (5), 38–45.
He, Q., Liu, J., Wang, S., Yu, J., 2020. The impact of COVID-19 on stock markets. Econ. Politi. Stud. 1–14.
Huang, Z., Huang, J., Gu, Q., Du, P., Liang, H., Dong, Q., 2020. Optimal temperature zone for the dispersal of COVID-19. Sci. Total Environ. 736, 139487.
India TV, 2020. Can Drop in Temperature Impact Covid Spread? Know From Health Expert. Retrieved from. https://www.indiatvnews.com/health/can-drop-in-temperature-impact-covid-spread-know-from-health-expert-667149.
Iqbal, N., Fareed, Z., Shahzad, F., He, X., Shahzad, U., Lina, M., 2020. The nexus between COVID-19, temperature and exchange rate in Wuhan city: new findings from partial and multiple wavelet coherence. Sci. Total Environ. 729, 138916.
Kumar, S., 2020. Will COVID-19 pandemic diminish by summer-monsoon in India? Lesson from the first lockdown. MedRxiv, 2020.04.22.20075499.
Liu, H., Manzoor, A., Wang, C., Zhang, L., Manzoor, Z., 2020a. The COVID-19 outbreak and affected countries stock markets response. Int. J. Environ. Res. Publ. Health 17 (8), 1–19.
Liu, J., Zhou, J., Yao, J., Zhang, X., Li, L., Xu, X., Zhang, K., 2020b. Impact of meteorological factors on the COVID-19 transmission: a multi-city study in China. Sci. Total Environ. 726, 138513.
Livemint, 2020a. Covid-19 May Be Lethal for India's Economy but it Ain't Bad for Rupee. Retrieved from. https://www.livemint.com/market/mark-to-market/covid-19-may-be-lethal-for-india-s-economy-but-it-ain-t-so-bad-for-rupee-11586407946514.html.
Livemint, 2020b. Rupee Slides to Record Low, Near 77 Per US Dollar. Retrieved from. https://www.livemint.com/.
Lyashenko, Vyacheslav, Mohammed, Omer Ibrahim Abdallah, Babker, Asaad Mohammed Ahmed, 2020. COVID-19 wavelet coherence data for some Gulf countries. GSC Biol. Pharmaceut. Sci. 11 (2), 166–174.
Molteni, M., 2020. Covid Winter Is Coming. Could Humidifiers Help? WIRED. Retrieved from. https://www.wired.com/story/covid-winter-is-coming-could-humidifiers-help/.
Ng, E.K.W., Chan, J.C.L., 2012. Interannual variations of tropical cyclone activity over the north Indian Ocean. Int. J. Climatol. 32 (6), 819–830.
OECD, 2020. COVID-19 and Global Capital Flows. Retrieved November 2, 2020, from OECD Report to G20 International Financial Architecture Working Group website. http://www.oecd.org/coronavirus/policy-responses/covid-19-and-global-capital-flows-2dc69002/.
Olayeni, O.R., Tiwari, A.K., Jahromi, R.S., Oladiran, O.I., 2014. Inflation, output gap, and money in Malaysia: evidence from wavelet coherence. Int. J. Comput. Econ. Econom. 4 (3/4), 320.
Oliveiros, B., Caramelo, L., Ferreira, N.C., Caramelo, F., 2020. Role of temperature and humidity in the modulation of the doubling time of COVID-19 cases. MedRxiv, 2020.03.05.20031872.
Park, J.E., Son, W.S., Ryu, Y., Choi, S.B., Kwon, O., Ahn, I., 2020. Effects of temperature, humidity, and diurnal temperature range on influenza incidence in a temperate region. Influenza Other Respir. Viruses 14 (1), 11–18.
Pequeno, P., Mendel, B., Rosa, C., Bosholn, M., Souza, J.L., Baccaro, F., Magnusson, W., 2020. Air transportation, population density and temperature predict the spread of COVID-19 in Brazil. PeerJ 8, e9322.
Prata, D.N., Rodrigues, W., Bermejo, P.H., 2020. Temperature significantly changes COVID-19 transmission in (sub)tropical cities of Brazil. Sci. Total Environ. 729, 138862.
Qi, H., Xiao, S., Shi, R., Ward, M.P., Chen, Y., Tu, W., Zhang, Z., 2020. COVID-19 transmission in Mainland China is associated with temperature and humidity: a time-series analysis. Sci. Total Environ. 728, 138778.
Quilodran, C.S., Currat, M., Montoya-Burgos, J.I., 2020. Climatic factors influence COVID-19 outbreak as revealed by worldwide mortality. MedRxiv, 2020.04.20.20072934.
Ravi, S., 2020. Impact of Covid -19 on children's education. J. Xidian Univ.
Richardson, P., 2020. Weekly Update: Global Coronavirus Impact and Implications. Counterpoint Research. Retrieved from. https://www.counterpointresearch.com/coronavirus-weekly-update/.
Sarkodie, S.A., Owusu, P.A., 2020. Impact of meteorological factors on COVID-19 pandemic: evidence from top 20 countries with confirmed cases. Environ. Res. 191, 110101 (August).
Sharif, A., Aloui, C., Yarovaya, L., 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. Int. Rev. Financ. Anal. 70, 101496 (April).
Sharma, G.D., Talan, G., Jain, M., 2020. Policy response to the economic challenge from COVID-19 in India : a qualitative enquiry. J. Publ. Aff. 1–16.
Shi, P., Dong, Y., Yan, H., Zhao, C., Li, X., Liu, W., Xi, S., 2020. Impact of temperature on the dynamics of the COVID-19 outbreak in China. Sci. Total Environ. 728 (77), 138890.
Statista, 2020. Change in Global Stock index Values during Coronavirus Outbreak 2020. Retrieved from. https://www.statista.com/statistics/1105021/coronavirus-outbreak-stock-market-change/.
Sui, L., Sun, L., 2016. Spillover effects between exchange rates and stock prices: evidence from BRICS around the recent global financial crisis. Res. Int. Bus. Finance 36, 459–471.
Tamerius, J., Nelson, M.I., Zhou, S.Z., Viboud, C., Miller, M.A., Alonso, W.J., 2011. Global influenza seasonality: reconciling patterns across temperate and tropical regions. Environ. Health Perspect. 119 (4), 439–445.
The Hindu, 2020. The Battle to Set Oil Prices. Retrieved from. https://www.thehindu.com/opinion/op-ed/the-battle-to-set-oil-prices/article31230648.ece.
The Week, 2020. America forgot the seasonality of COVID-19 — until it was too late. Retrieved from. https://theweek.com/articles/951998/america-forgot-seasonality-covid19–until-late.
Thorbecke, W., 2020. The impact of the COVID-19 pandemic on the U.S. Economy: evidence from the stock market. J. Risk Financ. Manag. 13 (10), 233.
Tiwari, A.K., Olayeni, O.R., Sherafatian-Jahromi, R., Adejonwo, O.S., 2019. Output gap, money growth and interest rate in Japan: evidence from wavelet analysis. Arthaniti: J. Econ. Theory Pract. 18 (2), 171–184.
Tobías, A., Molina, T., 2020. Is temperature reducing the transmission of COVID-19 ? Environ. Res. 186, 109553 (April).
Torrence, C., Compo, G.P., 1998. A practical guide to wavelet analysis. Bull. Am. Meteorol. Soc. 79 (1), 61–78.
Torrence, C., Webster, P.J., 1998. The annual cycle of persistence in the El Nño/Southern Oscillation. Q. J. R. Meteorol. Soc. 124 (550), 1985–2004.
UNCTAD, 2020. The Covid-19 Shock to Developing Countries : towards a " Whatever it Takes " Programme for the Two-Thirds.
Villarreal-Samaniego, D., 2020. COVID-19, oil prices, and exchange rates: a five-currency examination. SSRN Electron. J. 1–22.
Walid, C., Chaker, A., Masood, O., Fry, J., 2011. Stock market volatility and exchange rates in emerging countries: a Markov-state switching approach. Emerg. Mark. Rev. 12 (3), 272–292.
Wallis, P., Nerlich, B., 2005. Disease metaphors in new epidemics: the UK media framing of the 2003 SARS epidemic. Soc. Sci. Med. 60 (11), 2629–2639.
Wang, M., Jiang, A., Gong, L., Luo, L., Guo, W., Li, C., Li, H., 2020a. Temperature significant change COVID-19 transmission in 429 cities. MedRxiv (February 2019), 2020.02.22.20025791.
Wang, Y., Wang, Y., Chen, Y., Qin, Q., 2020b. Unique epidemiological and clinical features of the emerging 2019 novel coronavirus pneumonia (COVID-19) implicate special control measures. J. Med. Virol. 92 (6), 568–576.
Wilder-Smith, A., Chiew, C.J., Lee, V.J., 2020. Can we contain the COVID-19 outbreak with the same measures as for SARS? Lancet Infect. Dis. 3099 (20).
World Economic Forum, 2020. How the U.S. response to coronavirus affects other economies. Retrieved June 14, 2020, from. https://www.weforum.org/agenda/2020/05/how-the-u-s-response-to-coronavirus-is-forcing-the-hand-of-the-world-s-central-banks.
Wu, Y., Jing, W., Liu, J., Ma, Q., Yuan, J., Wang, Y., Liu, M., 2020. Effects of temperature and humidity on the daily new cases and new deaths of COVID-19 in 166 countries. Sci. Total Environ. 729, 139051.
Xie, J., Zhu, Y., 2020. Association between ambient temperature and COVID-19 infection in 122 cities from China. Sci. Total Environ. 724, 138201.
Yao, Y., Pan, J., Liu, Z., Meng, X., Wang, W., Kan, H., Wang, W., 2020. No association of COVID-19 transmission with temperature or UV radiation in Chinese cities. Eur. Respir. J. 55 (5).
Yarovaya, L., Brzeszczynski, J., Goodell, J.W., Lucey, B.M., Lau, C.K., 2020a. Rethinking financial contagion: information transmission mechanism during the COVID-19 pandemic. SSRN Electron. J.
Yarovaya, L., Matkovskyy, R., Jalan, A., 2020b. The effects of a "black swan" event (COVID-19) on herding behavior in cryptocurrency markets: evidence from cryptocurrency USD, EUR, JPY and KRW markets. SSRN Electron. J.
Zhang, D., Hu, M., Ji, Q., 2020. Financial markets under the global pandemic of COVID-19. Finance Res. Lett. (January).