Full length article

A time–frequency analysis of the impact of the Covid-19 induced panic on the volatility of currency and cryptocurrency markets

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ABSTRACT

We apply wavelet analyses to examine the impact of the Covid-19 fueled panic on the volatility of major fiat and cryptocurrency markets during January–May, 2020. There is high coherence between moves of the Coronavirus Panic Index and the price moves in Euro, British pound, and Renminbi currencies as well as movements of the Bloomberg Galaxy Crypto Index. The main conclusions for each index pair are quite similar and corroborate with our thesis that the cross-currency hedge strategies, which could work under normal market conditions, are likely to fail during the periods of global crisis, e.g., such as the Covid-19 pandemic. However, we document some important differences in currency markets behavior, which potentially could be used to design effective cross-currency hedges capable of withstanding adverse impacts of global financial and economic turmoil. Our findings could be of use for future development of financial policies and currency markets regulation rules.

1. Introduction

Currency and cryptocurrency markets represent a complex system in the domain of economics and finance (Yang et al., 2016; Bouri et al., 2019; Gomes and Gubareva, 2020; and the references therein). These studies of interdependence of foreign exchange markets and cryptocurrency markets have been attracting a vast research interest from the point of view of contagion, adversely impacting portfolio risk management, strategic asset allocation, and financial instruments pricing (Baumohl, 2019; Kristjanpoller and Bouri, 2019; Malik and Umar, 2019; Celeste et al., 2020).

On the other hand, financial markets worldwide have been severely affected by the global pandemic of Covid-19 (Al-Awadi et al., 2020; Ali et al., 2020; Godel, 2020; Haroon and Rizvi, 2020; Iqbal et al., 2020; Sharif et al., 2020; Zhang et al., 2020). In particular, the Covid-19 crisis has negatively impacted the potential role

of cryptocurrencies as diversifying investments (Liu, 2019; Tiwari et al., 2019; Conlon and McGee, 2020; Gil-Alana et al., 2020). Hence, the study of the fiat currencies and cryptocurrencies dynamics through the Covid-19 bear market and initial recovery from it provides a unique way to investigate the economic impact of the pandemic in the important domain of the financial system and its stability as a whole. Although the joint dynamics of conventional currencies, such as EUR, GBP, and RMB and of major cryptocurrencies had been explored in the recent past, see, e.g., Kristjanpoller and Bouri (2019), the impact of Covid-19 panic on currency and cryptocurrency markets remains to be duly addressed in academic literature. Therefore, it is desirable to analyze the behavior of cryptocurrencies compared to major fiat currencies to assess the potential capacity of cryptocurrencies to be used as a hedge for fiat currencies in the periods of global crisis, such as Covid-19 pandemic turmoil.

Based on the above rationale, we employ the wavelet coherence and wavelet phase difference techniques to investigate the impact of covid-19 induced panic on the fiat currency and cryptocurrency markets. We employ the panic level metrics given by the Ravenpack Coronavirus Panic Index (PI), and gauge its interdependence with the volatility exhibited by exchange rates of fiat currencies and cryptocurrencies, during the Covid-19 crisis over the first five months of the year 2020. The Ravenpack corona panic index is a unique index that is used as a proxy

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for the panic created by corona virus. The index measures the panic by the level of news related to panic and coronavirus. The wavelet techniques allow us to obtain the results in the form of time–frequency heatmaps containing the information on both coherence and time difference of the studied pairs of indices. Although there are many alternative approaches available for coherence and risk contagion studies, such as VaR, variance decomposition, time-varying connectedness approach, and so on, (Garcia and Araujo, 2013; Malik and Umar, 2019; and the references therein) our choice of the wavelet analysis is mainly based on the three following reasons.

First, the wavelet coherence analysis is capable of providing insights on the joint behavior of indices, not only along the sole dimension of time, but also over different investment time scales or so-called frequency periods, thus enabling to study various patterns of exchange rate movements, lead–lag relations, and comovements. Given the importance of frequency domain in this context, we resort to wavelet methods. Second, the wavelet technique does not require any strong assumption such as stationarity and can be used to capture both linear and non-linear effects. Third, wavelet methods can help us to decipher important conclusions, even for relatively short time series of data owing to the data availability related to the pandemic. All the above characterize the wavelet methodology as a robust approach, commonly employed to investigate coherence between various time series (e.g., Vacha and Barunik, 2012; Sun and Xu, 2018; Zaremba et al., 2019), which we use to study the causality relationships between the variations in levels of the Covid-19 panic and currencies and cryptocurrencies exchange rates.

Our motivation to explore the comparative behavior of the Covid-19 panic levels and the exchange rates in US$ of leading currencies and cryptocurrencies is related to the fact that both fiat currencies and cryptocurrencies, being simultaneously value stores and transaction means, are, nevertheless heavily affected by market expectations and speculations, which are always amplified by herd behavior in the periods of crisis.

The literature on the spillover, safe-haven and cross-market interdependence across assets and financial markets has attracted a lot of attraction since the supreme crisis of 2007 (Umar and Suleman, 2017; Riaz et al., 2019, 2020; Stereńczak et al., 2020; Naeem et al., 2020; Umar et al., 2018, 2019a,b,c; Zaremba et al., 2020; Kenourgios et al., 2020). The recent covid-19 pandemic has presented a unique challenge and inspired a new stream of literature focused on the impact of this pandemic on financial markets. Our research contributes to the incipient and, hence, insufficient literature: we document the currency markets reaction to the Covid-19 induced crisis. Our findings are important for the currency market players and regulators in their attempts to comprehend and forecast the behavior of currencies during the periods of global economic and financial distress, as we discuss the unique dynamics of Covid-19 crisis.

The contribution of our research to the contemporaneous state-of-art literature on currency markets is three-fold. First, we fill in the existing gap related to the lack of academic research on the dynamic interdependence maps of sentiment variables, such as panic levels, and the exchange rates in the fiat currency and cryptocurrency markets in the time–frequency perspective. Second, our paper adds to the current literature on currency market response to Covid-19 economic impacts. As our sample period covers the most recent global crisis caused by the pandemic, our finding can provide useful insights for investors, traders, risk managers, and regulators of the currency and cryptocurrency markets. Third, we document a high level of coherence between the panic level and the dynamics of leading fiat and crypto currencies, thus evidencing that cross-currency hedge strategies are likely to fail during the periods of major global financial stresses.

Table 1
Descriptive statistics for the time series of the selected exchange rates:.

	EUR	GBP	RMB	BGCI
Average	7.82	11.46	4.57	3.06
Standard deviation	4.48	6.47	1.81	2.30
Skewness	1.03	1.85	1.05	0.42
Kurtosis	0.02	3.00	0.95	(0.62)
Minimum	2.35	4.99	1.93	–
1st quartile	4.56	7.52	3.25	1.02
Median	6.57	9.37	4.26	3.08
3rd quartile	9.51	11.47	5.50	4.79
Maximum	19.48	34.48	9.60	9.24
Observations	103.00	103.00	103.00	103.00

Note. The table reports daily changes in the selected exchange rates for Jan–May 2020.

The rest of the paper is organized as follows. Section 2 discusses the data and the methodologies employed. Section 3 presents the results and provides their interpretation. Section 4 concludes.

2. Data and methods

To analyze interdependencies between the Covid-19 panic, measured by the Coronavirus Panic Index (PI), and diverse currencies and cryptocurrencies, we obtained daily values of the respective exchange rates expressed in US$ for comparison. The exchange rate time series covers the first five months of the year 2020. The Coronavirus index data is obtained from Ravenpack and it measures the panic by measuring the level of news that refers to panic or hysteria and coronavirus. The index value lies between 0 and 100, with 100 indicating the highest level of news talking about panic and coronavirus and 0 implying the lowest level. Apart from the PI, our dataset includes the volatility of three fiat currencies, EUR, GBP, and RMB, and the Bloomberg Galaxy Crypto Index (BGCI). The BGCI index is composed of ten major cryptocurrencies and is designed to measure the performance of the largest cryptocurrencies traded in US$. The BGCI is a market capitalization-weighted index, which includes cryptocurrencies such as Bitcoin, Ethereum, Monero, Ripple, and Zcash, among others. The index constituents are diversified across different categories of digital assets, including stores of value, mediums of exchange, smart contract protocols, and privacy assets. We extract the currency volatility data from Bloomberg. The choice of daily frequency for data analysis arises because the PI is available only on a daily basis and because the higher frequency intraday movements of exchange rates are outside of the scope of the current research.

Table 1 reports the summary statistics for the daily changes in currency and cryptocurrency exchange rates for EUR, GBP, RMB, and BGCI from the beginning of January to the end of May 2020.

To disentangle the multiscale interdependency between the PI and the currency and cryptocurrency foreign exchange rates in US$, we employ the wavelet coherence technique. The advantage of using wavelet methodology is that it allows us to simultaneously analyze the dependency in both time and frequency domain. We employ the continuous wavelet transformation to obtain squared wavelet coherency measures like those given by Torrence and Webster (1999) and Vacha and Barunik (2012). The wavelet coherence measures the correlation between a pair of variables in both the time and the frequency domains. The single coherence number for any day at any frequency from high (daily) to low (32-day period) is bounded by 0 (depicting zero correlation) and 1 (depicting perfect, i.e., the highest possible correlation between two time series). The wavelet coherence technique displays interdependence between two different time series; however, it is not the optimal approach to gauge the

lead–lag relationships between interdependent variables. To get a deeper insight into lead–lag relations among the PI and currency/cryptocurrency exchange rates, we employ the wavelet coherence phase difference technique following Torrence and Webster (1999) and more recent work by Sun and Xu (2018), Zaremba et al. (2019).

On the side of our main research line as a back-product, we dig deeper into the cryptocurrencies, investigating the PI impact on each of the ten leading cryptocurrencies separately. We study the following cryptocurrencies: Bitcoin (BTC); Lite Coin (XLC); Monero (XMR); Zcash (XZC); Ripple XRP token (XRP); EOS cryptocurrency (EOS); Dash (XDH), Ethereum Classic (XTH), Ethereum (XET); and BitCoin Cash (BTCC). However, the wavelet heatmaps through the Covid-19 crisis for each pair of PI-cryptocurrency are very similar to each other and to the PI-BGCI heatmaps. Therefore, we decided to exclude them from the main body of the article and present separately in Annex.

3. Results

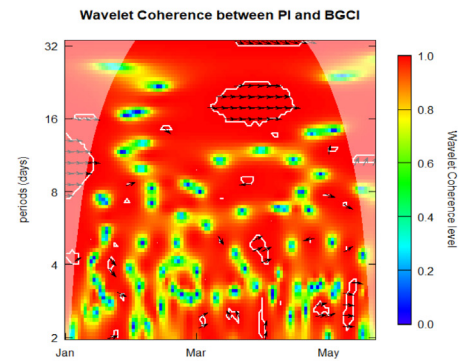### 3.1. Ravenpack Coronavirus Panic Index (PI) and Bloomberg Galaxy Crypto Index (BGCI)

Panels 1A and 1B of Fig. 1 display, respectively, the results for the wavelet coherence measure and phase-difference based lead–lag relationship between the Coronavirus Panic Index (PI) and the Bloomberg Galaxy Crypto Index (BGCI).

We begin our analysis by examining the wavelet coherence results between the PI and the BGCI in Panel 1A. The legend on the right-hand side shows the key for reading the heatmap. Time is displayed on the horizontal axis and frequency, or the length of the period of analysis in days is shown on the vertical axis. The interpretation of the graph is based on the color displayed for any date and frequency. In general, the warmer the color (yellow to red), the greater the coherence or interdependence between the indices. The cooler colors (blue to green) imply less coherence. For the PI-BGCI pair, we document medium to high coherence over the entire timescale, as Panel 1A appears to be predominantly red.

The time periods with higher coherence are seen starting with the second week of March and ending by the mid-April. It is worth noting that on March 6, the Organization of Petroleum Exporting Countries (OPEC) and Russia were unable to agree on an additional cut in production to stem the fall in crude prices after the Covid-19 epidemic, thereby causing an even faster decline on oil prices on March 9, which in turn further increased the volatility of financial markets. The observed drop of major stock indices on March 09 is also representative of a generalized market stress provoked by the Covid-19 pandemic. A partial recovery from this acute meltdown was observed in the first half of April, which is correctly reflected by Panel 1A.

Over the frequency scale, coherence is high across most frequencies, but more specifically, it changes from high to medium-low in the 3-days, 7-days, and 14-days frequency periods. This result represents a certain interest from the point of view of behavioral sciences, as the above phenomena of diminishing coherence for a set of frequencies exhibits, not constant but alternating patterns along the time scale. We posit that these spots of a rather low coherence represent the contrarian type of the behavior of market participants, being the impacts of trades realized by the so-called contrarians. These contrarians try to anticipate unexpected market moves in either direction and appear to be either wrong or right, however, being the first movers who trade currencies on assumptions different from those of the mainstream, captured by the PI. If they are right, the mainstream traders adjust to them, and if they are proved wrong, then they newly adjust themselves to the mainstream. A further research in this market

Panel 1A: Wavelet Coherence between the Ravenpack Coronavirus Panic Index (PI) and the Bloomberg Galaxy Crypto Index (BGCI).

Panel 1B: Phase Difference Relationship between the Coronavirus Panic Index (PI) and the Bloomberg Galaxy Crypto Index (BGCI)
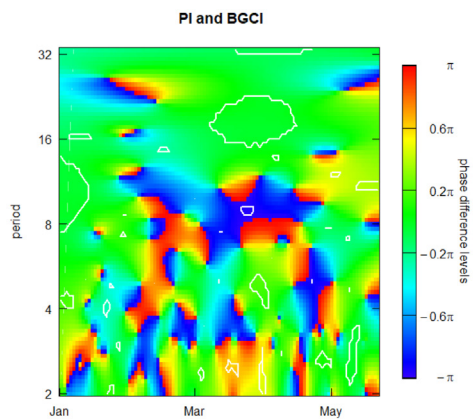

Fig. 1. Wavelet coherence and phase-difference based lead–lag relationship between the Ravenpack Coronavirus Panic Index (PI) and the Bloomberg Galaxy Crypto Index (BGCI).

behavior peculiarity is desirable, although the adjustment in one or two weeks seems to be plausible with the fact that the humans are used to cut the time in week-long intervals, along with days, months, and years.

We also identify causality and phase differences between the PI and the BGCI. Arrows indicate the phase differences between the PI and the BGCI moves. For example, → and ← indicate that both the PI and the BGCI are in phase and out of phase, respectively. ↗ and ↙ indicate that the PI moves are leading those of the BGCI, while ↘ and ↖ indicate that the PI moves are lagging those of the BCGI.

As shown in Panel 1A, we observe the most significant degree of comovement between the PI and the BGCI for frequency periods above two weeks in the second half of March and the first half of April. In accordance with our interpretation, already exposed a few paragraphs above, we associate this interval of the Covid-19 provoked crisis with the panic-leads-market phase. These highly aligned comovements serve as an indication that panic selling or panic buying leave almost no room for diversification strategies as the market is severely influenced by the so-called herd behavior and that those strategies, which could work under normal market conditions may fail during periods of crisis.

We also identify causality and phase differences between the PI and the BGCI moves. In Panel 1A, we observe the arrows →, signifying an in-phase relationship in the two-weeks-plus band,

Panel 2A: Wavelet Coherence between the Ravenpack Coronavirus Panic Index (PI) and the Euro currency (EUR).
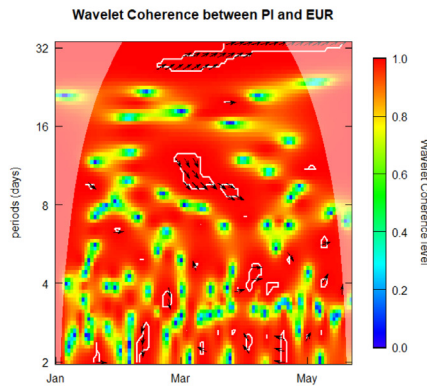
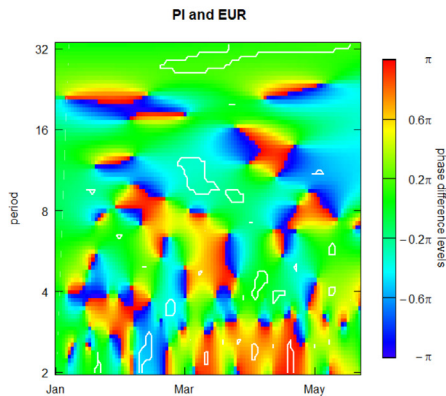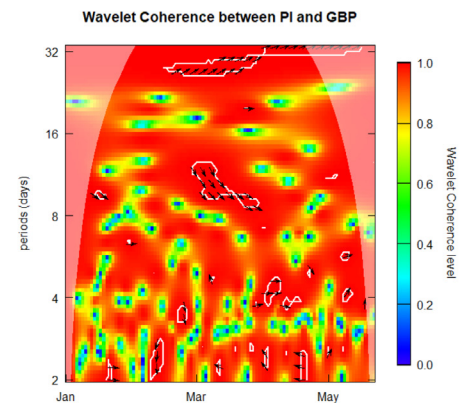Panel 2B: Phase Difference Relationship between the Coronavirus Panic Index (PI) and the Euro Currency (EUR).

Fig. 2. Wavelet coherence and phase-difference based lead–lag relationship between the Ravenpack Coronavirus Panic Index (PI) and the Euro currency (EUR).

Panel 3A: Wavelet Coherence between the Ravenpack Coronavirus Panic Index (PI) and the British pound (GBP).

Panel 3B: Phase Difference Relationship between the Coronavirus Panic Index (PI) and the British pound (GBP).
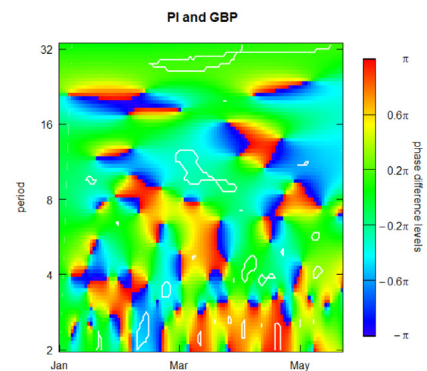

Fig. 3. Wavelet coherence and phase-difference based lead–lag relationship between the Ravenpack Coronavirus Panic Index (PI) and the British pound (GBP).

indicating the positive correlation between the PI and the BGCI during late March early April. We also see the spot of these arrows around mid-May in the 2- to −4-days band, indicating that the high frequency contrarian behavior is disappearing, most likely as traders see the positive initial signs of the economic recovery from the crisis, provoked by the Covid pandemic.

To gain further insight into the interdependency relationship, Panel 1B identifies the lead–lag relationship between the PI and the BGCI. These results also suggest that, in the second half of March and the first half of April, the PI predominantly leads the BGCI in the 1–2 weeks frequency band, see the blue cloud in the middle of Panel 1B. Interestingly enough, within the 1-week band we observe the alternating patterns suggesting unsynchronized behavior of the two indexes, most likely due to the arbitrage scamming efforts by the contrarian currency traders. However, the overall average tonality of Panel 1B could be characterized as green, bearing in mind that red/yellow spots on average are fairly compensated by blue zones. Such results may be considered broadly consistent with an interpretation of the cryptocurrency markets as very sensitive to the overall mood and susceptible to the mainstream expectations, especially during the periods of crisis, e.g., the Covid-19 pandemic. This finding could be of use for future financial policy and cryptocurrency markets regulation decisions.
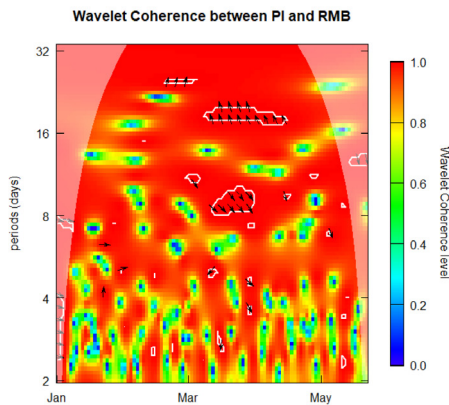
3.2. Coronavirus Panic Index (PI) and Euro currency rate (EUR)

Panels 2A and 2B of Fig. 2 display, respectively, the results for the wavelet coherence measure and phase-difference based lead–lag relationship between the Ravenpack Coronavirus Panic Index (PI) and the Euro currency (EUR) rate in US$.

The time periods with higher coherence are seen in March and April in 1-week-plus frequency band, see the red zone in the middle of Panel 2A, spread around the apogee of the pandemic-provoked meltdown, occurred in the middle of March.

Over the frequency scale, coherence is high across most frequencies, but more specifically, it changes from high to medium-low for the 3-days period and for the second week band. This result represents a certain interest from the point of view of behavioral sciences, as the above phenomena of diminishing coherence for a set of frequencies exhibits, not constant but alternating patterns along the time scale. We posit that these spots of a rather low coherence represent the contrarian type of the behavior of Euro currency market participants. A further research in this market behavior peculiarity seems to be desirable. It is worth mentioning that in the case of the Euro currency, such minicycles with average duration around 10 days are well noticeable (see small blue spots with greenish turquoise aureoles, about 14 from left to right in the 3-days band along all the analyzed period of approximately 140 days (almost 5 months)).

Panel 4A: Wavelet Coherence between the Ravenpack Coronavirus Panic Index (PI) and the Chinese Yuan Renminbi (RMB).

Panel 4B: Phase Difference Relationship between the Coronavirus Panic Index (PI) and the Chinese Yuan Renminbi (RMB).
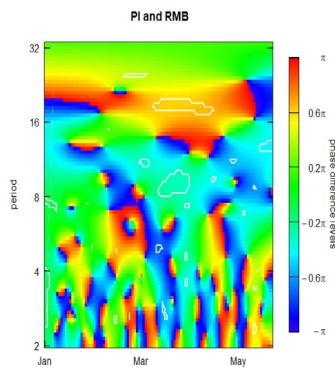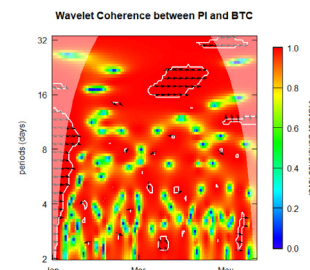

Fig. 4. Wavelet coherence and phase-difference based lead–lag relationship between the Ravenpack Coronavirus Panic Index (PI) and the Chinese Yuan Renminbi (RMB).

We also identify causality and phase differences between the PI and the EUR. As shown in Panel 2A, we observe the most significant degree of comovement between the PI and the EUR rate for the second week frequency band and for 1-month-plus band in March. In accordance with our interpretation, already exposed a few paragraphs above, we associate this interval of the Covid-19 provoked crisis with the apogee of the pandemic meltdown resulting in the panic-leads-market phase. These highly aligned co-movements serve as an indication that panic selling or panic buying leave almost no room for diversification strategies.

We also identify causality and phase differences between the PI and the EUR rate moves. In Panel 2A, we observe the arrows ↗ in the 1-month-plus band and ↘ in the 7- to −14-days band, signifying that the PI moves are, respectively, leading and lagging moves of the EUR rates. This result indicates that during the last month of the mounting up panic, the advances in the PI lead the EUR exchange rate, while the initial signs of reduction in the panic level were lagging the EUR currency moves. Seemingly, the EUR rate moves were firstly observed, then interpreted by the people as good signs, and only then reflected in the PI. This interpretation could be supported by the analysis of the two-weeks-plus frequency band, which reveals the positive correlation between the PI and the BGCI during late March–early April. We also see the spot of these arrows around mid-May in the 2- to −4-days band, indicating that the high frequency contrarian behavior is

Panel I.1A: Wavelet Coherence between the Ravenpack Coronavirus Panic Index (PI) and the Bitcoin (BTC).

Panel I.1B: Phase Difference Relationship between the Coronavirus Panic Index (PI) and the Bitcoin (BTC).
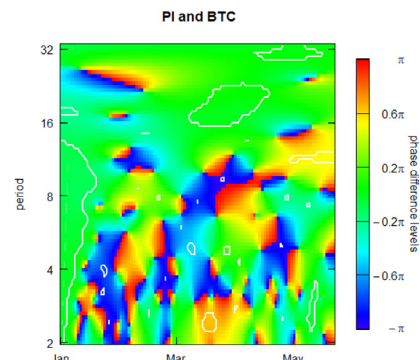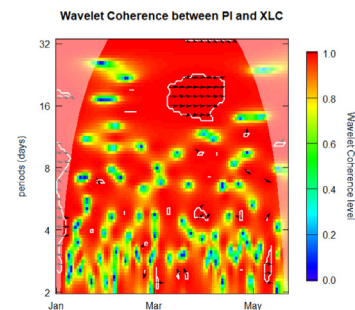

Fig. I.1. Wavelet coherence and phase-difference based lead–lag relationship between the Ravenpack Coronavirus Panic Index (PI) and the Bitcoin (BTC).

Panel I.2A: Wavelet Coherence between the Ravenpack Coronavirus Panic Index (PI) and the Lite Coin (XLC).

Panel I.2B: Phase Difference Relationship between the Coronavirus Panic Index (PI) and the Ethereum Lite Cash (XLC).
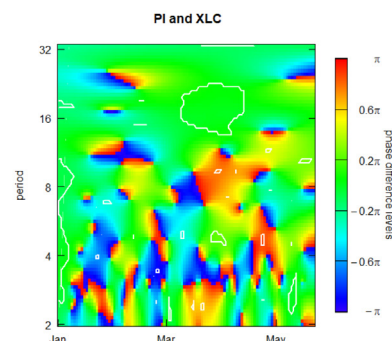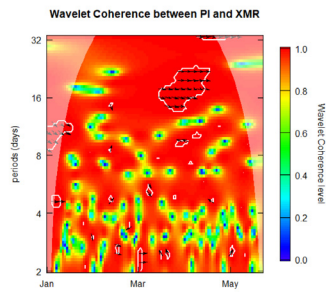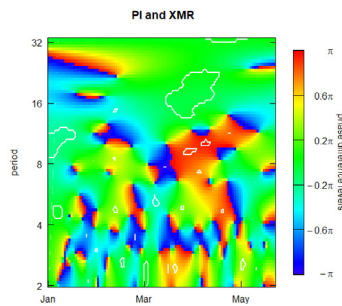

Fig. I.2. Wavelet coherence and phase-difference based lead–lag relationship between the Ravenpack Coronavirus Panic Index (PI) and the Lite Coin (XLC).

Panel I.3A: Wavelet Coherence between the Ravenpack Coronavirus Panic Index (PI) and the Monero cryptocurrency (XMR).

Panel I.4A: Wavelet Coherence between the Ravenpack Coronavirus Panic Index (PI) and the Zcash (XZC).

Panel I.3B: Phase Difference Relationship between the Coronavirus Panic Index (PI) and the Monero cryptocurrency (XMR).

Panel I.4B: Phase Difference Relationship between the Coronavirus Panic Index (PI) and the Zcash (XZC).

Fig. I.3. Wavelet coherence and phase-difference based lead–lag relationship between the Ravenpack Coronavirus Panic Index (PI) and the Monero cryptocurrency (XMR).

Fig. I.4. Wavelet coherence and phase-difference based lead–lag relationship between the Ravenpack Coronavirus Panic Index (PI) and the Zcash (XZC).

disappearing, most likely as traders see the positive initial signs of the economic recovery from the crisis, provoked by the Covid pandemic.

To gain further insight into the interdependency relationship, Panel 2B identifies the lead–lag relationship between the PI and the EUR. These results also suggest the following. First, in March and April the PI predominantly lags the EUR rate moves in the 2- to −3-days band. Second, in the 4- to −8-days band the PI predominantly lags behind the EUR rate only in March. Third, within the second week band, since March onwards, the PI predominantly leads the EUR rate moves, see the greenish-turquoise cloud becoming blue in the right-hand side in the middle of Panel 2B.

Interestingly enough within the 1-week band we observe the alternating patterns suggesting unsynchronized behavior of the two indexes, most likely due to the arbitrage scamming efforts by the contrarian currency traders. However, the overall average tonality of Panel 2B could be characterized as green, bearing in mind that the red/yellow spots on average seem to be fairly compensated by the blue zones. Such results may be considered broadly consistent with an interpretation of the EUR currency markets as very sensitive to the overall mood and susceptible to the mainstream expectations, especially during periods of crisis. This finding could be of use for future design of financial policies and currency markets regulation rules.

3.3. Coronavirus Panic Index (PI) and British pound (GBP)

Panels 3A and 3B of Fig. 3 display, respectively, the results for the wavelet coherence measure and phase-difference based lead–lag relationship between the Ravenpack Coronavirus Panic Index (PI) and the British pound (GBP) rate in US$. Both the panels – and
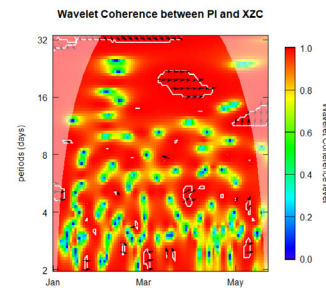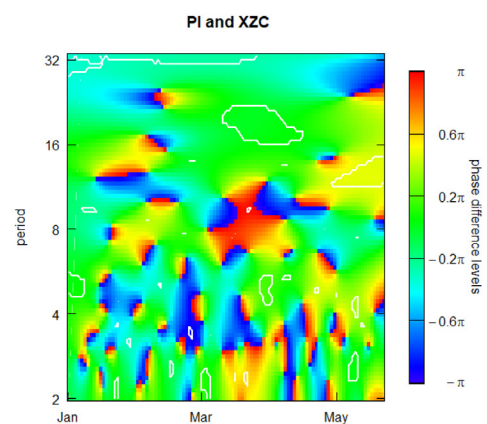
the conclusions from their analyses – are very similar to Panels 2A and 2B and the respective findings regarding the impact of the PI on the volatility of the Euro currency markets. It means that from the point of view of the currency markets behavior, GBP and EUR exchange rates in US$ exhibit very similar dynamics. The coherence, causality, and the phase differences during the Covid provoked market stress are obeying the same patterns, not really leaving a room for the GBP-EUR cross-currency hedge strategies, capable of withstanding adverse impacts of global financial and economic turmoil.

3.4. Coronavirus Panic Index (PI) and the Chinese Yuan Renminbi (RMB)

Panels 4A and 4B of Fig. 4 display, respectively, the results for the wavelet coherence measure and phase-difference based lead–lag relationship between the Ravenpack Coronavirus Panic Index (PI) and the Chinese Yuan Renminbi (RMB) in US$.

Similarly, to the PI-EUR and PI-GBP panels, the time periods with higher coherence are seen in March and April in 1-week-plus frequency band, see the red zone in the middle of Panel 4A, spread around the apogee of the Covid pandemic provoked meltdown, occurred in the middle of March. However, differently from previous cases, for the RMB we see an additional zone of pronounced higher coherence; see the horizontal red belt in the 5-to −6-days band, for the whole February–May period. This peculiarity of the RMB currency market may represent a potential opportunity for developing cross-currency strategies towards

Panel I.5A: Wavelet Coherence between the Ravenpack Coronavirus Panic Index (PI) and the Ripple XRP token (XRP).

Panel I.6A: Wavelet Coherence between the Ravenpack Coronavirus Panic Index (PI) and the EOS cryptocurrency (EOS).
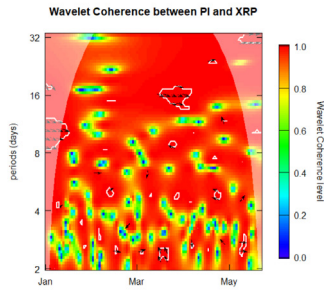
Panel I.5B: Phase Difference Relationship between the Coronavirus Panic Index (PI) and the Ripple XRP token (XRP).

Panel I.6B: Phase Difference Relationship between the Coronavirus Panic Index (PI) and the EOS cryptocurrency (EOS).
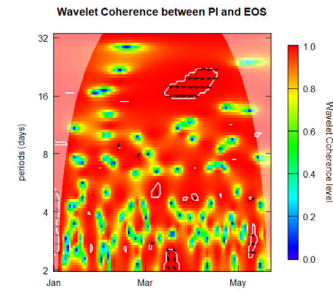

Fig. I.5. Wavelet coherence and phase-difference based lead–lag relationship between the Ravenpack Coronavirus Panic Index (PI) and the Ripple XRP token (XRP).
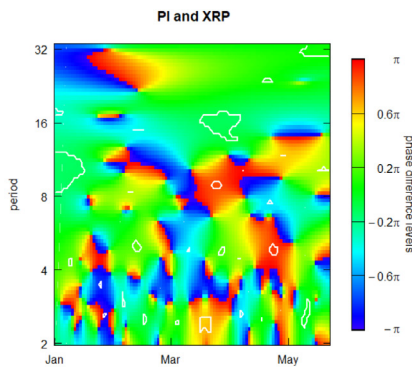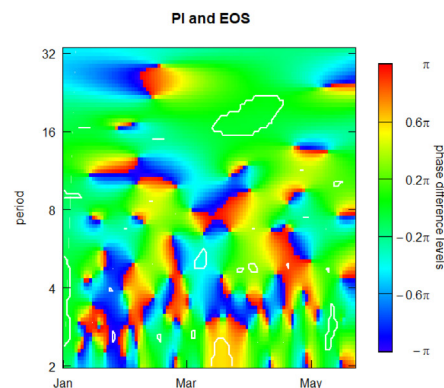
Fig. I.6. Wavelet coherence and phase-difference based lead–lag relationship between the Ravenpack Coronavirus Panic Index (PI) and the EOS cryptocurrency (EOS).

EUR and GBP, as such a belt is rather absent in their panels. Its understanding surely deserves to be addressed in further research.

Over the frequency scale, coherence is high in the 5-days-plus band, but more specifically, it changes from high to medium-low for the 1–4 days band. A rather low coherence for the 1-to −2-days high frequencies also represents a distinctive feature in comparison to the PI-EUR and PI-GBP panels, potentially allowing for designing cross-currency hedges. On the other hand, the observed phenomenon of diminishing coherence for the panel's bottom band, now similar to the PI-EUR and PI-GBP panels, exhibits not constant but alternating patterns along the time scale. We also ascribe such dynamics of low coherence to the traders-contrarians, and posit that apparently in the RMB currency market such traders are more actively undertaking efforts to bet and to beat the market in the periods of 1- to −2-days, which is consistent with the national inclination of Chinese people to gambling. A further research in this market behavior peculiarity seems to be desirable, especially as in the case of RMB rate the short minicycles of average duration about 10 days are especially well noticeable, see several small blue spots with greenish turquoise aureoles along all the analyzed period.

We also identify causality and phase differences between the PI and the RMB. As shown in Panel 4A, we observe the most significant degree of comovement between the PI and the RMB rate for the 8–10 days band in March and April and for the 2-weeks-plus band from March onwards. In accordance with our interpretation, already exposed a few paragraphs above, we associate this interval of the Covid-19 provoked crisis with the apogee of the pandemic meltdown resulting in the panic-leads-market phase. These highly aligned comovements serve as an indication that panic selling or panic buying leave little room for diversification strategies.

We also identify causality and phase differences between the PI and the RMB rate moves. In Panel 4A, we observe the arrows ↖ in the 2-weeks-plus band and ↘ in the 7- to −10-days band, signifying that the PI moves are lagging behind moves of the RMB rates. This result indicates that, seemingly, the RMB rate moves were firstly observed, then, they were interpreted by the people as bad or good signs, and, only afterwards, they became reflected in the PI.

To gain further insight into the interdependency relationship, Panel 4B identifies the lead–lag relationship between the PI and the RMB. These results also suggest that in March and April the PI predominantly lags behind the RMB rate moves in the 2-weeks-plus band, while in May this dynamics is changed. Now the PI leads the RMB rate moves, as the economic situation globally appears more promising.

Interestingly enough, within the 1-week band we observe the alternating patterns suggesting unsynchronized behavior of the two indices, most likely due to the arbitrage scamming efforts by the contrarian currency traders. However, the overall average tonality of Panel 4B could be characterized as green, bearing in mind that the red/yellow spots on average seem to be fairly compensated by blue zones. Such results may be considered broadly consistent with an interpretation of the RMB currency markets as very sensitive to the overall mood and susceptible to the mainstream expectations, especially during the periods of

Panel I.7A: Wavelet Coherence between the Ravenpack Coronavirus Panic Index (PI) and the Dash cryptocurrency (XDH).
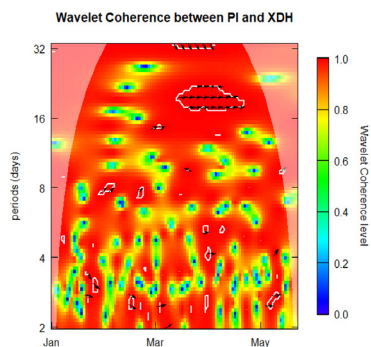
Panel I.7B: Phase Difference Relationship between the Coronavirus Panic Index (PI) and the Dash cryptocurrency (XDH).
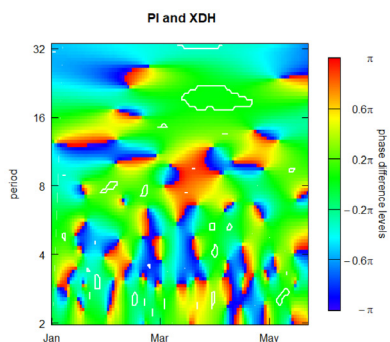

Fig. I.7. Wavelet coherence and phase-difference based lead–lag relationship between the Ravenpack Coronavirus Panic Index (PI) and the Dash cryptocurrency (XDH).
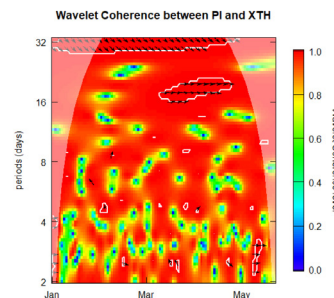
Panel I.8A: Wavelet Coherence between the Ravenpack Coronavirus Panic Index (PI) and the Ethereum Classic cryptocurrency (XTH).

Panel I.8B: Phase Difference Relationship between the Coronavirus Panic Index (PI) and the Ethereum Classic cryptocurrency (XTH).
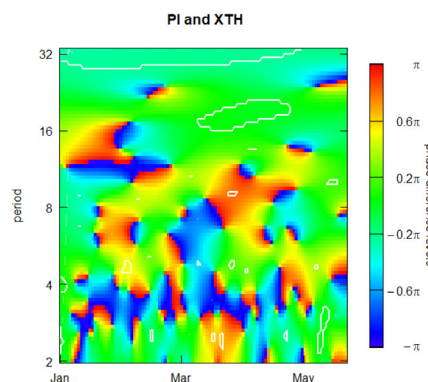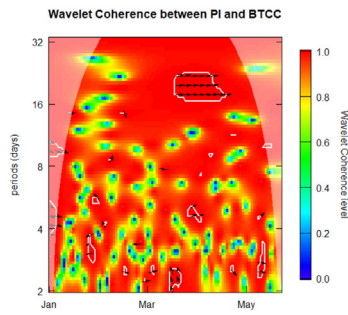

Fig. I.8. Wavelet coherence and phase-difference based lead–lag relationship between the Ravenpack Coronavirus Panic Index (PI) and the Ethereum Classic cryptocurrency (XTH).

crisis. This finding could be of use for future financial policy and currency markets regulation decisions.

4. Conclusion

This study has estimated the interdependence between the Coronavirus Panic Index (PI) and the exchange rates for a selected set of currencies and cryptocurrencies – EUR, GBP, RMB, and BGCI – over the first five-month period of the Covid-19 pandemic (January–May, 2020) using wavelet coherence and wavelet phase difference methodologies. All the PI-currency pairs display similar patterns along the time and frequency scales in the respective heatmaps implying high coherence and interdependence around the apogee in the mid-March of the Covid-19 panic. However, we observe some peculiarities of RMB behavior in comparison to EUR, GBP, and BGCI. This indicates that RMB could be eligible for designing cross-currency hedge strategies, which could work in the periods of global crisis, as evidenced by the Covid pandemic. Nevertheless, on average, the movements of the exchange rates are well synchronized with the panic level dynamics, which serves as an alert that cross-currency hedges designed to work under normal market conditions are most likely to fail while crossing periods of global financial turmoil.

Our findings have important implications for policy makers, investors and regulators. The adverse impact of the pandemic on all currency markets shows that governments and policy makers need to devise robust solution for a systemic crisis such as the

Covid-19. Our results support Sharif et al. (2020) conclusion that government intervention to reduce uncertainty is of paramount importance. The relatively better performance of the RMB may be attributed to the fact that the management of the RMB is performed by the central bank. Similarly, our findings can be useful for currency traders and investors to design cross-currency hedge strategies particularly during the periods of extreme turmoil. The negative impact of the Covid-19 on all currencies under review implies that investors need to look for other investment alternatives, which can act as safe havens during such turbulent periods. Lastly, regulators need to be more vigilant during such financial turmoil episodes and may need to provide active support to the forex markets. We leave the issue of the exact nature of these policies and their potential effectiveness under various scenarios as a topic for further research.

Panel I.9A: Wavelet Coherence between the Ravenpack Coronavirus Panic Index (PI) and the BitCoin Cash (BTCC).

Panel I.9B: Phase Difference Relationship between the Coronavirus Panic Index (PI) and the BitCoin Cash (BTCC).
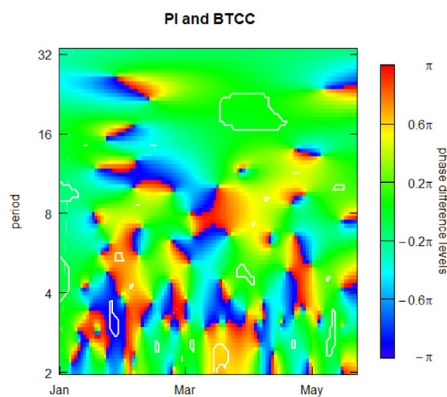

Fig. I.9. Wavelet coherence and phase-difference based lead–lag relationship between the Ravenpack Coronavirus Panic Index (PI) and the BitCoin Cash (BTCC).

Panel I.10A: Wavelet Coherence between the Ravenpack Coronavirus Panic Index (PI) and the Ethereum (XET).

Panel I.10B: Phase Difference Relationship between the Coronavirus Panic Index (PI) and the Ethereum (XET).

Fig. I.10. Wavelet coherence and phase-difference based lead–lag relationship between the Ravenpack Coronavirus Panic Index (PI) and the Ethereum (XET).
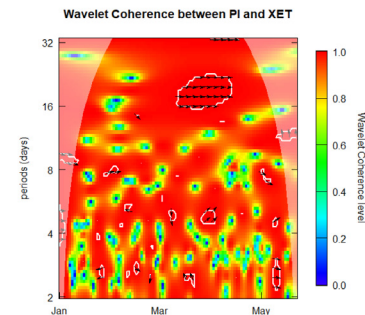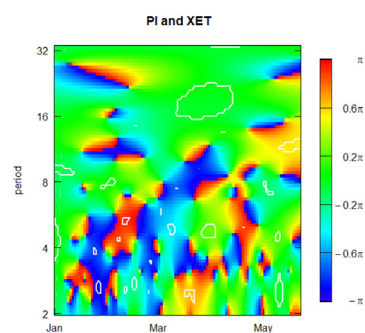
Acknowledgments

Annex I. Individual heatmaps for the wavelet coherence and phase-difference between the Ravenpack Coronavirus Panic Index (PI) and ten selected cryptocurrencies

See Figs. I.1–I.10.

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