

Research Article

Illiquidity, Uncertainty Indices, and COVID-19 Outbreak Conditions: Empirical Evidence from the US Financial Market

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In this paper, wavelet coherences and quantile autoregressive distributed lag (QARDL) approaches are used to study the effect of economic policy uncertainty (EPU), infectious disease EMV tracker (IDEMV), and implied volatility (VIX) on illiquidity during the tranquil and COVID-19 epidemic periods in the US financial market. Our results show that lagged EPU, current VIX, and lagged VIX positively affect illiquidity during the calm period, while the lagged EPU and current VIX decrease illiquidity during the pandemic period. Furthermore, infectious diseases in the financial market during the pandemic crisis play a significant role in instantaneously improving liquidity, while it was not significant during the tranquil period. Similarly, we suggest that with the combined effect of the EPU and the VIX, the uncertainty caused by implied volatility decreases liquidity in a lagged and contemporaneous manner, while an improvement in liquidity is revealed in the case of the EPU.

1. Introduction

Understanding the dynamics of liquidity in the financial market is very important for market participants and policymakers. Many authors such as Chordia et al. [1], Ma et al. [2], Tissaoui and Ftiti [3], and Tissaoui et al. [4] have suggested that a better assessment of liquidity can give investors the opportunity to improve their trading strategy by monitoring liquidity risks. This in turn allows for an effective and efficient use of funds and gives them greater certainty about the future. Policymakers can promote legislation to prevent the evaporation of stock market liquidity and illegal insider trading. In response to these important concerns, a massive number of empirical studies have demonstrated the existence of various variables that have influenced stock liquidity.

The first group of authors focused on specific securities-related variables such as trading volume, number of trades,

volatility, and order imbalance (e.g., Bagehot [5]; Kyle [6]; Chordia et al. [7]; Chai et al. [8]; Dey and Radhakrishna [9]; Tissaoui and Ftiti [3]; Bedowska-Sójka and Echaust [10]; Xu et al. [11]; Xu et al. [12]; and Chuliá et al. [13]). These papers have shown a significant relationship between these variables and liquidity. For example, Leirvik et al. [14] examined the relationship between market liquidity and stock returns in the Norwegian stock market from 1983 to 2015. They used a simple linear model on panel data. The empirical results confirm that the level of market liquidity has a negligible impact on stock returns. The second group of papers focused on systematic variables such as common liquidity (e.g., Chordia et al. [15]; Brockman and Chung [16]; Hasbrouck and Seppi [17]; Karolyi et al. [18]; Foran et al. [19]; Tissaoui et al. [3]; and Anagnostidis and Fontaine [20]). The evidence from these studies showed that the commonality of liquidity substantially affects the liquidity of stocks. Corporate governance and securities laws have been identified by the third

group of authors as additional determinants of stock market liquidity. Espinosa et al. [21] confirmed the positive relationship between corporate governance variables and stock market liquidity between 1994 and 2000 in the Spanish context. In a study of the impact of voluntary disclosure on stock market liquidity in France, Lakhel [22] found that quarterly disclosure is a good indicator of stock market liquidity. The empirical results confirm that quarterly disclosure increases stock market liquidity by reducing bid-ask spreads and increasing trading volume.

A fourth group emphasized variables related to behavioural finance. According to a trading model by Kyle [6], the behaviour of the three participants (insiders, market makers, and noisy traders) has an important impact on liquidity. In addition, it is worth noting that investor sentiment has a direct and indirect effect on liquidity. The direct effect of investor sentiment is confirmed by Liu [23] as affecting liquidity through two channels. The first one is where the investor is confident in the market liquidity flows. In theoretical discussions, De Long et al. [24] showed that there are two types of investors in the market: some investors are called noise traders who trade on sentiment and irrational beliefs, while other investors are considered rational investors who trade on economic fundamentals. The authors further argue that the beliefs of irrational traders are driven by noise and interpreted as information. Therefore, an increase in irrational beliefs among these noisy investors, which is accompanied by an increase in sentiment, will generate an expansion of trading and, consequently, an increase in liquidity. The second channel is related to irrational market makers. Otherwise, a higher sentiment among investors increases the stock market liquidity [25]. The indirect effect of investor sentiment is associated with investor psychology. Overconfidence and investor sentiment are two factors that influence the investor's decision and consequently the stock market liquidity. Empirically, the relationship between investor sentiment and stock market liquidity in both NYSE and AMEX from 1976 to 2007 was studied by Liu [23]. He referred to the methodology of Amihud [26]. Their empirical results show that stock market liquidity is better when the investor sentiment index increases. A more recent paper by Debata et al. [27] suggests that local and foreign investor sentiment and liquidity are significantly associated.

The remaining group of researchers has looked at the effect of uncertainty indices on the financial market as well as on other markets such as oil and gold. Bouri et al. [28] examined the predictive power of the implied volatility of commodity markets and major developed stock markets on the implied volatility of individual BRICS stock markets. Using daily data from 16 March 2011 to 7 October 2016, they employed the new Bayesian graphical structural vector autoregressive (BGSVAR) model developed by Ahelegbey et al. [29]. The empirical result reports that the predictability of individual implied volatilities in the BRICS is generally found to be a function of the implied volatilities of the global and intra-group stock as well as the role of commodity market volatility is marginal, except for South Africa. Similarly, Sayed and Bouri [30] considered the spillover

effects of global economic policy uncertainty (GEPU) and oil price volatility on the volatility of stock market indices of oil exporters and importers in developed and emerging economies. Results show that the spillover effect of GEPU on oil exporters is rather smaller than the effect on oil importers for both developed and emerging economies.

Similarly, Bouri et al. [31] investigated the predictive power of daily newspaper-based index of uncertainty associated with infectious diseases (EMVID) for the volatility of gold market returns via the heterogeneous autoregressive realized volatility (HAR-RV) model. Their results show that EMVID increases the realized volatility (RV) substantially at the highest level of statistical significance within the sample. This finding improves the accuracy of forecasts of the realized volatility of gold at short, medium, and long time horizons. Finally, Dutta et al. [32] studied the relationship between uncertainty indices and crude oil volatility from January 1990 to December 2019. They used quantile regressions to estimate risk spillover effects between the US equity markets and the WTI crude oil market, allowing for a detailed examination in low and high volatility states of the crude oil market. Their results indicate a significant impact of EMV trackers on oil market volatility during periods of high oil volatility, while the impact is mostly insignificant when the oil market is less volatile.

However, the emerging coronavirus (COVID-19) pandemic in December 2019 has motivated academic researchers to examine the effect of this outbreak on the financial market [33]. For example, the US financial market registered substantial and record losses in the first quarter of 2020. The Daily FT [34] supported this finding by stating that "the Dow Jones and S&P, both of which reflect the stock prices of a range of companies in the US, have collapsed by more than 20%." Ozili and Arun [35] also highlighted the dramatic fall in the value of the S&P 500 index, which reached more than \$5 trillion in one week, from 24 to 28 March, while the ten largest companies lost more than \$1.5 trillion in the same period. The present crisis has a distinctive characteristic compared to all previous crises. Increasingly, investors are concerned not only about the value of their own assets and investments but also about their personal security and well-being and that of their families. According to Tissaoui and Zaghdoudi [36], this situation leads to great uncertainty even for the most sophisticated traders. This has been heightened among traders as they see for the first time that a pandemic outbreak has generated volatility and dynamic shocks in the equity and oil markets. Sharif et al. [37] pointed out that the sudden onset of a COVID-19 pandemic led to fatal turbulence in US financial markets, involving higher levels of equity volatility than those experienced in the previous financial crises of October 1987, December 2008, and the 1929 crash.

In line with this work, many academics have tried to examine the effect of variables measuring uncertainty in the stock market during the COVID-19 pandemic crisis. They suggested many variables representing uncertainty such as economic policy uncertainty (EPU), infectious disease EMV tracker (IDEMV), and implied volatility (VIX) (e.g., Wang et al. [38]; Alqahtani and Martinez [39]; Bai et al. [40]; and

Al-Awadhi et al. [41]). The predictive power of IDEMV and VIX for the volatility market in France, the UK, and Germany, for example, was examined by Li et al. [42]. Using a HAR model, the authors found that IDEMV and VIX are good predictors of volatility during the COVID-19 pandemic.

Using a GARCH-MIDAS model, Bai et al. [40] explored the effect of IDEMV on market volatility in the US, China, and the UK. They found a positive and significant impact of IDEMV on volatility. In the same vein of the literature, Wang et al. [38] investigated the useful information content of the EPU and VIX to forecast the future volatility of 19 stock market indices. Based on a HAR model, the authors showed that the VIX dominates the EPU in predicting volatility during the coronavirus pandemic. The results of Alqahtani and Martinez [39] supported this conclusion by indicating that the EPU is a significant factor for a higher level of risk premium and price fluctuations, especially when the economy is down.

As a result, there is a considerable literature on the impacts of uncertainty indices and their links to financial markets, but it suffers from several shortcomings. First, they ignore the impact of uncertainty indices on market liquidity under various market conditions. Second, previous studies are silent on the impact of infectious diseases on the stability of financial markets, as this hazard may affect the ability of investors to better compose their speculative strategies and implement their short and long-term hedging instruments. Third, the study of the relationship between market liquidity and uncertainty in the United States is addressed using standard time series models. However, there is no research on this relationship that refers to time-frequency models.

The aim of this research, therefore, is to build on the results of previous studies and fill in the gaps in current academic work by examining the effects of uncertainty indices on liquidity during the COVID-19 pandemic and by comparing them with their effects during the calm period. To achieve this, we apply a quantile autoregressive distributed lag (QARDL) test and wavelet methods on a daily dataset. As a first step, we opt for the QARDL time series model developed by Cho et al. [43] in order to simultaneously test the short and long-term connectivity between the related variables which have a mixed order of integration and produce robust results when the normality of the model variables is not respected.

Cho et al. [43] and Zhan et al. [44] showed that this type of model is suitable for examining the short and long-term connectivity between variables on quantiles as it is flexible to take into account many stylized facts in the data such as non-linearity and non-normal distributions and it allows for the small sample size of the data. Formally, the QARDL model is able to estimate both stationary and non-stationary data and is convenient for dealing with asymmetric relationships between variables. This favours QARDL over the linear ARDL model which did not take this advantage into account. In our study, the main advantage gained by using the QARDL method is that it enables us to examine whether different levels of uncertainty indices may have different effects on illiquidity in the US financial market. As we are

assessing the study of long and short-term dynamics between uncertainty indices and illiquidity, the QARDL model will be the most appropriate model.

Following this, to further analyse the effect of uncertainty indices on illiquidity, we suggest the so-called wavelet approach to effectively test for co-movements as well as the lead-lag link between various variables in the time-frequency domain [36, 45]. Other researchers, including Sharif et al. [37], have reported that wavelet methods are used consistently, regardless of small sample sizes. In our study, these wavelet techniques allow to study the correlation and motion between different variables not only in time but also at different scales and thus provide more information than the original QARDL models. We therefore exploit these tools to better understand the dynamic relationship between illiquidity and uncertainty indices during pandemic and tranquility periods. Our study contains some original and novel contributions compared to previous studies. First, it is a pioneering work that investigates the effects of the EPU, VIX, and IDEMV on market illiquidity. To the best of our knowledge, no study has explored the separate and simultaneous effects of uncertainty indices on the liquidity of the US financial market. Second, our research adds to the above works on investigating the short and long-run effects of uncertainty indices on US market liquidity using a QARDL model and the wavelet approach during the pandemic period and the tranquility period. There are two reasons for focusing on the US financial market. The first reason is that the US financial market is the largest stock market in the world, with a market capitalization of just over US\$27.7 trillion in December 2021. The second reason is that the US financial market is seen as one of the main sources of the spread of volatility and uncertainty to other markets [37]. Thus, with the increase in COVID-19 cases over the world and especially in the US, the US financial market is now always in a state of collapse and tipping, while government processes that would have previously supported market stability to return to its tranquil state have been interpreted as confusing and indicative of dangerous market conditions.

Our paper has several important implications, including the following. (i) It provides a detailed and comprehensive overview of the influence of COVID-19 on the stability of the US financial market. (ii) It helps US authorities and listed companies to better understand the effects of uncertainty on US stock market illiquidity, so that they can respond with pertinent measures and mechanisms. (iii) It helps investors to better understand the conditions of the US stock market during the stock market surge and to compare them with the calm period in order to establish the appropriate investment policy: short (sell) or long (buy) positions to adopt.

The remainder of this article is organised as follows. Section 2 presents the materials and methods. The empirical results are presented in Section 3. Section 4 presents a detailed discussion and implications.

2. Materials and Methods

2.1. Data. The data sample consists of daily values of economic policy uncertainty (EPU), the infectious disease EMV tracker (IDEMV), implied volatility (VIX), and market

illiquidity in the US. Baker et al. [46, 47] were the first to develop the EPU and IDEMV, respectively. The EPU represents the number of articles covering news in major newspapers related to the economy, uncertainty, monetary and trade policies, and financial regulation in the US (https://www.policyuncertainty.com/us_monthly.html). The IDEMV (https://www.policyuncertainty.com/infectious_EMV.html) is the number of newspaper articles that contain terms on E: {financial, economy, economic}; M: {"Standard and Poor's," "stock market," equity, equities}; V: {risk, risky, volatility, volatile, uncertainty, uncertain}, and ID: {epidemic, pandemic, H5N1, H1N1, virus, seas, sars, ebola, flu, disease, coronavirus}. The data are available on the EPU website. Second, the VIX is the implied volatility index of the Chicago Board Options Exchange [36]. It was originally developed by Whaley [48] as a proxy for fear sentiment or a measure of volatility or uncertainty in the financial market. The data are downloaded from the CBOE website (<http://www.cboe.com/vix>). Finally, using the trading data for the S&P 500 index, we computed the main dependent variable (market illiquidity) as follows. We consider the Amihud illiquidity ratio as representing illiquidity. We calculate it as follows: $L_t = |r_t|/p_t \times V_t$ with r_t , p_t , and V_t denoting the daily return, the closing price on day t , and the trading volume on the same day, respectively.

Descriptive statistics are presented in Table 1 for both the pandemic and tranquil periods. The skewness test showed that the skewness values are greater than 0, which means that the distributions of the variables are skewed. Furthermore, a leptokurtic distribution is shown for all variables except for the EPU (the distribution is platykurtic when the value is less than 3) during the pandemic period since the kurtosis values are greater than 3. Table 2 shows a lower correlation between the explanatory variables, except for the relationship between the IDEMV and the VIX during the pandemic period (0.76) since the correlation coefficient is higher than 0.70. This indicates that the IDEMV and the VIX are dependent and that we cannot test them jointly. This is synonymous with the non-appearance of multicollinearity.

The results of the unit root tests are shown in Table 3. In the tranquil period, the PP test showed that the null hypothesis of the unit root is not accepted for all variables in level, which means that these variables are stationary at I(0). During the pandemic period, the unit root tests showed that the variables AL, RVT, EPU, and IDEMV are stationary at I(0), whereas the VIX appears stationary at first difference.

2.2. Methods

2.2.1. Benchmark Model: The QARDL Model. Our analysis begins by studying the dynamic connectivity between the US illiquidity market and the uncertainty indices (VIX, EPU, and IDEMV) across quantiles during the pandemic and tranquility periods. We apply the QARDL model proposed by Cho et al. [43] which generalizes the ARDL (Stoian and Iorgulescu [49] and Malik et al. [50] justify the use of ARDL model since it allows a great flexibility regarding the level of integration; so, all variables need not be integrated in the

same order; it may be stationary at I(0) or I(1) or a combination of both; in addition, with a small sample of data, the ARDL model can be used to estimate long and short-term dynamics between different variables) framework of Pesaran et al. [49] using the quantile regression method of Koenker and Bassett [50].

The QARDL model is methodologically better than linear models for at least three reasons. First, the model allows for location asymmetry in that the parameters can depend on the location of the dependent variable, market illiquidity, in its conditional distribution. Second, the QARDL model simultaneously treats the long-run relationship between policy uncertainty (EPU), infectious disease (IDEMV), implied volatility (VIX), and the dependent variable and its associated short-run dynamics across a range of quantiles of market illiquidity. Third, the QARDL framework allows the cointegrating coefficients to vary over the quantile of innovation from shocks. However, this methodological adaptation is a trade-off for the study's contribution to policymaking. Different levels of policy uncertainty, infectious disease, and implied volatility are expected to have varying influences on market illiquidity. The QARDL approach can therefore address the problem of policy formulation and, in doing so, contribute to the finance literature from a contextually focused methodological perspective. Therefore, the QARDL method allows the study of long-run quantile-dependent relationships between related variables that have a mixed order of integration and produces robust results when the normality of variables in the model fails. The ARDL error correction form is given by

$$\Delta Y = \alpha + \zeta(Y_{t-1} - \beta X_{t-1}) + \sum_{j=1}^{p-1} \gamma_j \Delta Y_{t-j} + \sum_{j=1}^{p-1} \delta_j \Delta X_{t-j} + \varepsilon_t, \quad (1)$$

where ΔY donates the first difference of the dependent variable, $X_t = (X_{1,t}, \dots, X_{K,t})'$ represents the $K \times 1$ regressors vectors which are not cointegrated among themselves, (p, q) are the lag orders, α gives the intercept, ζ denotes the speed of the adjustment to the long-run equilibrium, β indicates the long-run parameters, γ, δ represent the short-run parameters, and ε is the error term.

Referring to Cho et al. [37], the QARDL model can be written as follows:

$$\begin{aligned} \Delta Y = \alpha + \zeta(\tau)(Y_{t-1} - \beta(\tau)'X_{t-1}) + \sum_{j=1}^{p-1} \gamma_j(\tau)\Delta Y_{t-j} \\ + \sum_{j=1}^{p-1} \delta_j(\tau)' \Delta X_{t-j} + \varepsilon_t(\tau), \end{aligned} \quad (2)$$

where $\tau \in (0, 1)$ and $\varepsilon_t(\tau)$ is defined as $Y_t - Q_{Y_t}(\tau/F_{t-1})$, where $-Q_{Y_t}(\tau/F_{t-1})$ is the τ^{th} quantile of Y_t conditional in the smallest σ -field, F_{t-1} is generated by $\{X'_t, Y_{t-1}, X'_{t-1}, \dots\}$, and the optimal lag order of p and q is selected using the Bayesian information criterion (BIC). Based on equation (2), our QARDL model is given by the following.

Individual effect of uncertainty index on the illiquidity:

TABLE 1: Descriptive statistics.

	Mean	Median	Max	Min	SD	Skewness	Kurtosis	Jarque-Bera	Observations
Panel A: tranquil period									
AL	51.1	26.6	386.8	0.0	67.5	2.1	8.6	739.8	364
EPU	108.9	100.3	386.2	4.1	52.3	1.2	5.8	216.5	364
IDEMV	0.6	0.0	5.7	0.0	0.8	2.1	9.5	920.2	364
VIX	15.3	14.9	25.5	11.5	2.6	1.0	3.8	65.6	364
Panel B: pandemic period									
AL	124.9	60.8	1337.4	0.0	184.7	2.9	13.8	2275.762	366
EPU	303.6	276.8	861.1	22.3	160.7	0.7	3.2	33.12278	366
IDEMV	22.6	19.0	112.9	0.0	17.2	1.5	6.5	318.8119	366
VIX	28.9	26.4	82.7	12.1	12.1	1.6	6.6	357.5087	366

Note. Table 1 reports descriptive statistics including mean, median, standard deviation (SD), skewness, kurtosis, minimum (Min), maximum (Max) Jarque-Bera (JB), and number of observations (Obs) of daily market innovations of illiquidity and uncertainty indices. The tranquil period runs from 01 January 2019 to 30 December 2019. The pandemic period runs from 31 December 2019 to 31 December 2020.

TABLE 2: Correlation matrix.

	AL	EPU	INFECT	VIX
Panel A: tranquil period				
AL	1.00	0.02	-0.05	0.39
EPU		1.00	0.03	0.36
INFECT			1.00	-0.03
VIX				1.00
Panel B: pandemic period				
AL	1.00	0.04	0.20	0.52
EPU		1.00	0.69	0.57
INFECT			1.00	0.76
VIX				1.00

Note. Table 2 reports the correlation between all variables: the illiquidity market and the uncertainty indices. The tranquil period extends from 01 January 2019 to 30 December 2019. The pandemic period is from December 31, 2019, to December 31, 2020.

$$\begin{aligned}
\Delta AL &= \alpha + \zeta(\tau) \left(AL_{t-1} - \beta^{EPU}(\tau)' EPU_{t-1} \right) + \sum_{j=1}^{p-1} \gamma_j(\tau) \Delta AL_{t-j} + \sum_{j=1}^{p-1} \delta_j(\tau)' \Delta EPU_{t-j} + \varepsilon_t(\tau), \\
\Delta AL &= \alpha + \zeta(\tau) \left(AL_{t-1} - \beta^{VIX}(\tau)' VIX_{t-1} \right) + \sum_{j=1}^{p-1} \gamma_j(\tau) \Delta AL_{t-j} + \sum_{j=1}^{p-1} \delta_j(\tau)' \Delta VIX_{t-j} + \varepsilon_t(\tau), \\
\Delta AL &= \alpha + \zeta(\tau) \left(AL_{t-1} - \beta^{IDEMV}(\tau)' IDEMV_{t-1} \right) + \sum_{j=1}^{p-1} \gamma_j(\tau) \Delta AL_{t-j} + \sum_{j=1}^{p-1} \delta_j(\tau)' \Delta IDEMV_{t-j} + \varepsilon_t(\tau).
\end{aligned} \tag{3}$$

Combined effect of uncertainty indices on the illiquidity:

$$\begin{aligned}
\Delta AL &= \alpha + \zeta(\tau) \left(AL_{t-1} - \beta^{VIX}(\tau)' VIX_{t-1} - \beta^{EPU}(\tau)' EPU_{t-1} \right) \\
&\quad + \sum_{j=1}^{p-1} \gamma_j(\tau) \Delta AL_{t-j} + \sum_{j=1}^{p-1} \delta_j(\tau)' \Delta VIX_{t-j} + \sum_{j=1}^{p-1} \delta_j(\tau)' \Delta EPU_{t-j} + \varepsilon_t(\tau), \\
\Delta AL &= \alpha + \zeta(\tau) \left(AL_{t-1} - \beta^{IDEMV}(\tau)' IDEMV_{t-1} - \beta^{EPU}(\tau)' EPU_{t-1} \right) \\
&\quad + \sum_{j=1}^{p-1} \gamma_j(\tau) \Delta AL_{t-j} + \sum_{j=1}^{p-1} \delta_j(\tau)' \Delta IDEMV_{t-j} + \sum_{j=1}^{p-1} \delta_j(\tau)' \Delta EPU_{t-j} + \varepsilon_t(\tau),
\end{aligned} \tag{4}$$

TABLE 3: Unit root tests.

		AL	EPU	IDEMV	VIX
Panel A: tranquil period (PP)					
At level					
With constant	t-Statistic	-16.6092	-13.3368	-18.0249	-4.9418
	Prob.	0.0000	0.0000	0.0000	0.0000
With constant and trend	t-Statistic	-16.6078	-13.3210	-18.3519	-4.9714
	Prob.	0.0000	0.0000	0.0000	0.0003
Without constant and trend	t-Statistic	-14.5554	-3.4240	-16.8918	-1.4937
	Prob.	0.0000	0.0007	0.0000	0.1266
		***	***	***	n0
At first difference					
With constant	t-Statistic	d(AL)	d(EPU)	IDEMV	d(VIX)
	Prob.	-88.1957	-95.4565	-109.3908	-23.9863
With constant and trend	t-Statistic	-87.9956	-96.8844	-109.4468	-24.0661
	Prob.	0.0001	0.0001	0.0001	0.0000
Without constant and trend	t-Statistic	-88.4932	-95.0832	-109.2957	-23.9140
	Prob.	0.0001	0.0001	0.0001	0.0000
		***	***	***	***
Panel B: pandemic period (PP)					
At level					
With constant	t-Statistic	-15.0292	-7.9223	-9.3105	-2.2678
	Prob.	0	0	0	0.1831
With constant and trend	t-Statistic	-14.8418	-7.9117	-9.3057	-2.3986
	Prob.	0	0	0	0.3796
Without constant and trend	t-Statistic	-12.7257	-1.9886	-4.7286	-0.6669
	Prob.	0	0.0449	0	0.4278
		***	**	***	n0
At first difference					
With constant	t-Statistic	d(AL)	d(EPU)	d(IDEMV)	d(VIX)
	Prob.	-83.5912	-72.3359	-57.482	-23.3603
With constant and trend	t-Statistic	-83.7616	-79.0071	-58.3894	-23.4216
	Prob.	0.0001	0.0001	0.0001	0
Without constant and trend	t-Statistic	-83.7527	-72.2676	-57.3512	-23.3889
	Prob.	0.0001	0.0001	0.0001	0
		***	***	***	***

Note. Table 3 reports the unit root statistics of all variables: the illiquidity market and the uncertainty indices. The tranquil period covers the period from 01 January 2019 to 30 December 2019. The pandemic period starts on 31 December 2019 and ends on 31 December 2020. * Significant at 10%; ** significant at 5%; *** significant at 1%; no, not significant.

where AL is the market illiquidity, whereas EPU, IDEMV, and VIX represent, respectively, the economic policy uncertainty (EPU), the infectious disease EMV tracker (IDEMV), and the implied volatility (VIX). Δ AL, Δ EPU, Δ IDEMV, and Δ VIX are, respectively, the difference values of AL, EPU, IDEMV, and VIX.

2.2.2. Wavelet Coherence Approach. We first examine the relationship between the illiquidity and uncertainty indices of the US market in the pandemic and tranquility periods using the QARDL model. Although it is proven to be

effective in considering the interaction between short and long-term variables, this class of model is unable to deal with the complex structure caused by the non-linearity and spectral characteristics of the time series and the association between very short, short, medium, and long-term variables.

(1) Discrete Wavelet Transform. Unlike Fourier transform, consider simultaneous frequency components with time information of a signal. For the wavelet analysis, we understand between two kinds of wavelet transform. The first one is orthogonal identified as the discrete wavelet transform (hereafter, DWT) while the second one is non-orthogonal

named as the maximal overlap discrete wavelet transform (hereafter, MODWT). The DWT of a time series is an appropriate tool that allows one to investigate the multiscale characteristics of this time series. The DWT decomposes a given time series into a set of equally orthogonal wavelet basis functions. This is the form where any wavelet transform is discretely sampled. The DWT of a signal (X) is a suitable method that allows one to analyse the multiscale characteristics of this signal. The main objective of this transform is to decompose a signal into a set of regularly orthogonal wavelet basis functions. For Galegati [51], the MODWT is assimilated to a slender variation of the DWT. This approach is a linear filtering process that allows transforming a time series into parameters, which are inherent to deviations across scales. Moreover, in contrast to the DWT, the MODWT can oversample the data and therefore amplifies the resolution of signal at elevated scales. This permits us to obtain all-out information regarding the changeability of the time series. The MODWT is appropriate to estimate the scaling and wavelet coefficients $\tilde{w}_{j,t}$ and $\tilde{v}_{j,t}$. Formally, they are expressed as follows:

$$\begin{aligned}\tilde{w}_{j,t} &= \frac{1}{2^{j/2}} \sum_{l=0}^{L-1} \tilde{h}_{j,l} X_t, \\ \tilde{v}_{j,t} &= \frac{1}{2^{j/2}} \sum_{l=0}^{L-1} \tilde{g}_{j,l} X_{t-l},\end{aligned}\quad (5)$$

where $h_{j,t}$ and $g_{j,t}$ show the level wavelet and scaling filters, respectively. The MODWT wavelet and scaling filters are directly engendered from the DWT filter. These two components are, respectively, shown as

$$\begin{aligned}\tilde{h}_{j,l} &= \frac{h_{j,l}}{2^{j/2}}, \\ \tilde{g}_{j,l} &= \frac{g_{j,l}}{2^{j/2}}.\end{aligned}\quad (6)$$

When we consider X as a second-order stationary stochastic process with nil mean, the wavelet variance at any scale j is given as the variance of the wavelet coefficients at scale j and specified as

$$\sigma_{X,j}^2 = \frac{1}{2\tau_j} \text{var}(w_{j,t}). \quad (7)$$

Using MODWT, a signal is decomposed using Daubechies filter of length eight. According to Dash and Maitra [52], the Daubechies filter produces parameters, which exhibit better uncorrelatedness through scales and generates better results. Generally, the series are decomposed into wavelets' parameters ranging from D_1 to D_5 . In the present research, the connectedness between mispricing and investor sentiments is analysed for various frequencies, shorter scales, respectively, corresponding to the first decomposition D_1 (2–4 days) and second one D_2 (4–8 days), medium scales corresponding to D_3 (8–16 days), and long-run scales corresponding to D_5 (32–64 days) and D_4 (16–32)

decompositions. It is also worth noting that at higher frequencies, the outliers existing pass away with the lower frequencies.

2.2.3. The Continuous Wavelet Transform. The CWT offers a simultaneous localization in time and frequency domain. Referring to Nunes and Rua [53] and Baruník et al. [54], the CWT is given by

$$W_x(u, s) = \int_{-\infty}^{\infty} x(t) \frac{1}{\sqrt{s}} \overline{\psi\left(\frac{t-u}{s}\right)} dt. \quad (8)$$

Specifically, $W_x(u, s)$ is found by projecting the specific wavelet $\psi(\cdot)$ on the considered time series. With reference to the CWT, we recognize three measures, which allow to analyse a signal jointly in the time-frequency domain, namely, the wavelet power spectrum, cross-wavelet power, and wavelet coherence.

(1) Bivariate Wavelet Coherence. Different wavelet methods have been used to assess the relationship between illiquidity, economic policy uncertainty, implied volatility, and the infectious disease tracker indices. The aims behind opting for different wavelets tools can be explained by their ability to spot and follow time scale varying outlines. The wavelet tool evaluates time series' spectral features as a time function and exposes how time series' periodic constituents differ with time. Also, the wavelet tool allows to visualize the association between the variables across different frequencies and over time space.

One of the main advantages of the wavelet analysis is its ability to show hidden processes of developing cyclic trends and patterns related to financial and economic time series. In addition, due to its capacity to visualize the exact timing and scale of shocks, the wavelet coherence analysis also provides an insightful understanding of the lead-lag relationships between the variables during different band of scales (short, middle, and long-term run) and over time.

Note that the investors are heterogeneous and that the heterogeneous investment horizons support the existence of several scale bands (high scales and low scales). Thus, investors make portfolio management decision differently around different frequency ranges. More explicitly, short-term investors will be concerned with short-term time series coherency localized at low scales, whereas long-term investors are more interested in high scales. In this study, we have chosen different wavelet tools, namely, bivariate, partial, and multiple wavelet coherence, among the different approaches of wavelet to opt for in our investigation. Mathematically, the method of cross wavelets has the ability to decompose initially and then restructure $x(t)$ function [53] as follows:

$$x(t) = \frac{1}{C_\Psi} \int_0^\infty \left[\int_{-s}^s w_x(u, s) \Psi_{u,s}(t) du \right] \frac{ds}{s^2}, \quad s > 0. \quad (9)$$

Across series in a domain of time-frequency, the approach of wavelet coherence is a suitable tool in computing the coefficients of local correlation. The absolute smoothed

cross wavelet value is utilized to quantify wavelet coherence, standardized by the product of each series smoothed individual wavelet power spectrum.

$$R^2(u, s) = \frac{|S(s^{-1}W_{xy}(u, s))|^2}{S(s^{-1}|W_x(u, s)|^2)S(s^{-1}|W_y(u, s)|^2)} \quad (10)$$

The wavelet coherence gives the localized correlation coefficient between these two signals over time and across frequencies. Evidently, the wavelet coherence has the ability to faithfully detect the co-movements between signals over different investment horizons. From equation (10), S gives the smoothing parameter. $R^2(u, s)$ is like the correlation coefficient which meets the ensuing dissimilarity $0 \leq R^2(u, s) \leq 1$. When the squared wavelet coherence value is close to zero, this indicates that the correlation between the two time signals is weak. Also, a correlation coefficient value close to the unit indicates the existence of strong correlation.

(2) *Multiple Wavelet Coherence*. In addition to wavelet coherence analysis, we use partial and multiple techniques of wavelet (hereafter, PWC and MWC, respectively). Both methods have the potential to include control variables in a multivariate framework, whereas other wavelet approaches such as cross-wavelet coherence and wavelet coherence do not provide this possibility.

Partial wavelet coherence allows to identify the wavelet coherency between two variables after cancelling out the effect of a third variable which represents their common dependence, whereas multiple wavelet coherence is helpful

in looking for the wavelet coherence of multiple independent variables on the dependent variable. Also, multiple wavelet is able to detect areas of co-movements between variables in the time-frequency space. By employing the multivariate wavelets, the low-frequency oscillations' biasness is eliminated which is apparently seen in estimates of power spectrum of wavelet (see Liu et al. [55] and Veleda et al. [56]). Lastly, these multivariate wavelets permit the enclosure of another (third) variable termed as conditioning factor, which is ignored in methods of bivariate wavelet. Likewise, the two variables' combined effect on a third variable is not recognized by the technique of bivariate wavelet coherence. The principle of the partial wavelet coherence approach consists of detecting the wavelet coherence between two time series after eliminating the power of a third one. According to Mihanovic et al. [57], partial wavelet coherence is analogous to a simple correlation, and it will be expressed as

$$RP^2(y, x_1, x_2) = \frac{|R(y, x_1) - R(y, x_2) \cdot R(y, x_1)^*|^2}{[1 - R(y, x_2)^2][1 - R(x_2, x_1)]^2} \quad (11)$$

Multiple wavelet coherence and multiple correlations are more similar, which are meaningful to explore the multiple explanatory variables' impacts on an explained variable. By following the wavelet coherence application, multiple wavelet coherence detailed in the below equation is used, which is similar to multiple correlations. The multiple wavelet coherence helps to assess the multiple variables' combined effects on a particular dependent variable.

$$RM^2(y, x_2, x_1) = \frac{R^2(y, x_1) + R^2(y, x_2) - 2R_e[R(y, x_1) \cdot R(y, x_2)^* \cdot z(x_1, x_2)^*]}{(1 - R(x_1, x_2))} \quad (12)$$

The smoothing parameter is referred to as γS , in the above equation. The coefficient of squared wavelet-coherence (CSWC) satisfies the inequality requirement of $0 \leq R^2(u, s) \leq 1$. When a value of $R^2(u, s)$ is approaching zero, correlation is weak, and it suggests that the value of $R^2(u, s)$ approaching one signifies a high correlation. For the reasons mentioned earlier, the method of variable inspection in terms of duration and frequency is regarded as the most appropriate one. In addition, two-phase variables of the time series *i.e.* $\phi_{x,y}$ can be utilized to distinguish between the phases' relationships between these two time series variables. In this phase difference, the position of the pseudo-cycle is determined by

$$\phi_{x,y} = \tan^{-1} \left(\frac{\Im\{W_n^{xy}\}}{\Re\{W_n^{xy}\}} \right) \text{ with } \phi_{x,y} \in [-\pi, \pi]. \quad (13)$$

The arrow directions reveal the phase connection. If the arrows are pointing to the right (resp. left), it means the two variables are positively (negatively) connected. Furthermore, if the arrows approach the right and up (resp. down), the

variable x is leading (resp. lagging). On the other hand, if the arrows move to the left and up, the first variable x is lagging, and the correlation is negative. Still, if the arrows go to the left and down, the first variable x is leading, and the correlation is negative.

In all wavelet graphs below, the frequency is transformed to a time unit (daily) in the vertical axis and time (month or year) in the horizontal axis. In these plots, the black contour highlights the most significant region at 5% level as compared to the red noise. The high power zone is delimited by the coin of influence (COI), which is shown by a lighter color.

3. Empirical Results

3.1. QARDL Empirical Results. We first assess the interaction between illiquidity and uncertainty indices using the QARDL model during the quiet period when no hazards can affect market stability. For the individual effects of the uncertainty indices on the illiquidity market, Tables 4–6

TABLE 4: QARDL estimation results: tranquil period (independent variable: EPU).

Quantile (τ)	0.25		0.50		0.75	
Variables	Coeff	Pr ($> t $)	Coeff	Pr ($> t $)	Coeff	Pr ($> t $)
Short run						
Const	0.1963	0.8464	21.3693	0.0106**	26.3775	0.1319
AL_1	-0.9938	0.0000***	-0.9495	0.0000***	-0.8800	0.0000***
EPU	-0.0272	0.0002***	-0.2332	0.0001***	-0.1394	0.2682
EPU_1	0.0032	0.6809	0.0636	0.3143	0.0324	0.8070
EPU_2	0.0173	0.0267**	0.1086	0.0894*	0.1997	0.1368
EPU_3	0.0075	0.3336	0.0628	0.3267	0.1478	0.2720
EPU_4	0.0123	0.0961*	0.0141	0.8159	0.2059	0.1060
Long run						
EPU_1	-0.0274	0.0002***	-0.2456	0.0001***	-0.1584	0.2720
EPU_1.1	0.0032	0.6807	0.0670	0.3157	0.0368	0.8073
EPU_2.1	0.0174	0.0261**	0.1144	0.0896*	0.2269	0.1406
EPU_3.1	0.0076	0.3327	0.0661	0.3243	0.1679	0.2685
EPU_4.1	0.0124	0.0949*	0.0148	0.8156	0.2339	0.1039

Note. Table 4 reports the QARDL estimation results of the effect of EPU on the illiquidity market during the tranquil period that spans from January 01, 2019, to December 30, 2019. *Significant at 10%; **significant at 5%; ***significant at 1%.

TABLE 5: QARDL estimation results: tranquil period (independent variable: VIX).

Quantile (τ)	0.25		0.50		0.75	
Variables	Coeff	Pr ($> t $)	Coeff	Pr ($> t $)	Coeff	Pr ($> t $)
Short run						
Const	-25.2174	0.0000***	-99.0549	0.0000***	-164.2426	0.0011***
AL_1	-0.9823	0.0000***	-1.0034	0.0000***	-1.0581	0.0000***
AL_2	-0.0414	0.0001***	-0.2121	0.0000***	-0.1307	0.2516
AL_3	-0.0445	0.0000***	-0.0600	0.1790	-0.0642	0.5666
AL_4	-0.0518	0.0000***	-0.1484	0.0009***	-0.0617	0.5800
VIX	0.8705	0.1791	8.6879	0.0023***	13.3339	0.0611*
VIX_1	1.5240	0.0248**	1.2874	0.6632	3.7439	0.6143
Long run						
AL_2	-0.0421	0.0001***	-0.2113	0.0000***	-0.1236	0.2548
AL_3	-0.0453	0.0000***	-0.0598	0.1744	-0.0607	0.5628
AL_4	-0.0528	0.0000***	-0.1479	0.0009***	-0.0584	0.5793
VIX	0.8862	0.1789	8.6582	0.0027***	12.6013	0.0715*
VIX_1	1.5515	0.0233**	1.2830	0.6612	3.5382	0.6088

Note. Table 5 reports the QARDL estimation results of the effect of VIX on the illiquidity market during the tranquil period that spans from January 01, 2019, to December 30, 2019. *Significant at 10%; **significant at 5%; ***significant at 1%.

TABLE 6: QARDL estimation results: tranquil period (independent variable: IDEMV).

Quantile (τ)	0.25		0.50		0.75	
Variables	Coeff	Pr ($> t $)	Coeff	Pr ($> t $)	Coeff	Pr ($> t $)
Short run						
Const	0.0000	1.0000	14.2360	0.0229	71.4837	0.0000***
AL_1	-1.0000	0.0000***	-0.8988	0.0000***	-0.8515	0.0000***
IDEMV	0.0000	1.0000	-5.0280	0.2073	-8.7134	0.2067
IDEMV_1	0.0000	1.0000	7.1495	0.0721	5.6660	0.4092
IDEMV_2	0.0000	1.0000	-4.1803	0.2914	-9.9595	0.1466
IDEMV_3	0.0000	1.0000	5.1488	0.2083	-1.4442	0.8382
IDEMV_4	2.8173	0.0097***	10.2229	0.0131**	6.8548	0.3345
Long run						
IDEMV	0.0000	1.0000	-5.5942	0.2054	-10.2326	0.2054
IDEMV_1	0.0000	1.0000	7.9547	0.0739	6.6539	0.4121
IDEMV_2	0.0000	1.0000	-4.6510	0.2931	-11.6959	0.1533
IDEMV_3	0.0000	1.0000	5.7286	0.2107	-1.6960	0.8379
IDEMV_4	2.8173	0.0094***	11.3741	0.0138**	8.0499	0.3373

Note. Table 6 reports the QARDL estimation results of the effect of IDEMV on the illiquidity market during the tranquil period that spans from January 01, 2019, to December 30, 2019. *Significant at 10%; **significant at 5%; ***significant at 1%.

report the variation of the error correction model (ECM) cointegration parameter $\zeta(\tau)$ across quantiles (represented by AL_1). The ECM parameters appear significant and negative for all quantiles. This is synonymous with a very high speed of change from short-term disequilibrium to long-term equilibrium. Therefore, there is a long-term interaction between the variables. Furthermore, the results show that the speed of adjustment increases with the quantiles in the case of the VIX; however, the opposite is true for the EPU and the IDEMV.

Specifically, for the effects of EPU, Table 4 shows that in both the short term and long term, EPU is negative and significant at the 1% level for the ρ_1 and ρ_2 quantiles in instantaneous time. Consequently, a 1% increase in the EPU decreases AL by 2% in the first quantile and by 23% in the second quantile. Similarly, in the long run, 1% increase in EPU generates a decrease in AL by 2% in ρ_1 and 24% in ρ_2 . This means that the information content of the EPU index improves the liquidity of the US market in tranquil times. On the other hand, our results show that the lagged EPU in the short and long run is positive and significant. In the short run, a 1% increase in EPU_2 and EPU_4 increases AL by 1.7% and 1.2% in the first quantile and by 10% in the second quantile, respectively.

Similar results are also shown in the long term. A 1% increase in EPU_2 and EPU_4 increases AL by 1.7% and 1.2% in the first quantile and by 11% in the second quantile, respectively. This suggests that the information content of the lagged EPU contributes to the decrease in US market liquidity in the lower and middle quantiles. This implies that persistent economic policy uncertainty may render market stability difficult in terms of liquidity. Table 5 presents the results of the estimation of the VIX effects. In the instantaneous time frame, the findings shown in Table 5 indicate that the VIX is positively significant at the 1% significance level in both the short and long run for the second and last quantiles. In the short run, when the VIX increases by 1%, the AL increases by 868% and 1333% in the middle and top quantiles, respectively. This implies that illiquidity increases in magnitude as τ varies towards the upper quantiles, while a significant and positive effect of the VIX on illiquidity is detected in lag 1. A 1% increase in VIX generates an increase in AL of 152% in the lower quantile. Similarly, the same result is shown for the long term level. We show that, at the instantaneous level, a 1% increase in the VIX increases the AL by 865% and 1260%, respectively, in the middle and last quantiles. On the other hand, for the lagged level, a significant and positive effect of the VIX on illiquidity is found at lag 1. Moreover, in the first quantile, a 1% increase in VIX produces a 155% increase in AL. These results suggest that the current arrival of VIX information in the US market produces a decrease in short-term and long-term liquidity as τ varies towards higher quantiles. Similarly, our results clearly show that the information content of the lagged VIX contributes to the decrease in short and long-term liquidity. However, this result is only revealed in the first quantile. For the effects of IDEMV, we have indicated in Table 6 that no significant association is detected between IDEMV and AL for both the short and long-term levels, except in lag 4 where

a significant relationship between IDEMV and illiquidity is observed at the first quantile. These results highlight that the explanatory power of the uncertainty generated by the infectious disease is insignificant in explaining liquidity during the tranquil period.

We now turn to the discussion of the simultaneous effects of the uncertainty indices on the illiquidity market. As shown in Tables 7 and 8, the adjustment of the cointegration parameter of the error correction model (ECM) (represented by AL_1) is negative and significant for all quantiles. This implies the existence of a rapid convergence to the long-run equilibrium. For the simultaneous effects of the EPU and VIX on illiquidity, Table 7 shows that in instantaneous level, the VIX is significant at 5 and 1% for ρ_1 , ρ_2 , and ρ_3 in the short run and long run. Specifically, a 1% increase in VIX increases the level of AL by 191%, 877%, and 1615%. Similarly, in the long run, 1% of an increase in the VIX produces an increase in AL by 195%, 868%, and 1437%.

However, the EPU is negatively significant in both the short term and long term at the 1% significance level for the first and second quantiles only. A 1% increase in the EPU decreases AL by 6.1% and 13% in the short run and by 6.3% and 13% in the long run. As for the lagged level, the cointegration coefficient of VIX in lag 1 is found to be insignificant in the short run and long run at all quantiles. However, the lagged EPU appears insignificant at all quantiles, except at the first quantile where the cointegration coefficient is negative and significant. As can be seen from the above results, the explanatory power of the VIX is improved when estimated with the EPU.

Regarding the combined effects of the EPU and the IDEMV on illiquidity, Table 8 shows that the EPU is significant at the 1% level in the short run and long run for the first and second quantiles. A 1% increase in the EPU decreases AL by 3% and 20% in the short run and by 3% and 21% in the long run at quantiles ρ_1 and ρ_2 . However, the contemporary IDEMV is not significant in the short term and long term in the tranquil period at all quantiles. Furthermore, the results show that the IDEMV positively affects illiquidity in lags (1), (3), and (4) at the first quantile and lag (4) at the middle quantile. This implies that the lagged IDEMV can be used to predict illiquidity in the US financial market.

Identical results are proven in the pandemic condition. Tables 9–11 show that the cointegration parameter $\zeta(\tau)$ across quantiles (represented by AL_1) is significant and negative when considering only individual effects. This indicates a long-run interaction between the variables. Specifically, an improvement in the speed of adjustment is more pronounced in the case of the VIX than in the cases of the EPU and the IDEMV across quantiles. Table 9 also illustrates the impact of the EPU on illiquidity. In instantaneous time, the table shows that the EPU is negatively significant at 1% and 5% significance levels in both the short term and long term. Thus, a 1% increase in EPU reduces AL by 10% and 30% in the short run and by 14% and 52% in the long run for the middle and upper quantiles.

Although the lagged EPU appears positive and significant in the short term and long term for all quantiles, in the

TABLE 7: QARDL estimation results: tranquil period (independent variables: EPU and VIX).

Quantile (τ)	0.25		0.50		0.75	
Variables	Coeff	Pr ($> t $)	Coeff	Pr ($> t $)	Coeff	Pr ($> t $)
Short run						
Const	-19.3420	0.0010***	-97.6988	0.0000***	-165.1745	0.0003***
AL_1	-0.9785	0.0000***	-1.0112	0.0000***	-1.1233	0.0000***
AL_2	-0.0410	0.0022***	-0.1959	0.0000***	-0.1089	0.2947
AL_3	-0.0414	0.0018***	-0.0611	0.0758*	0.0437	0.6697
AL_4	-0.0687	0.0000***	-0.1528	0.0000***	-0.0957	0.3516
VIX	1.9122	0.0225**	8.7795	0.0001***	16.1512	0.0134**
EPU	-0.0618	0.0011***	-0.1363	0.0058***	-0.1477	0.3136
VIX_1	0.3140	0.7174	1.6812	0.4582	3.9019	0.5639
EPU_1	0.0432	0.0227***	0.0446	0.3659	-0.2271	0.1233
Long run						
AL_2	-0.0419	0.0021***	-0.1937	0.0000***	-0.0969	0.2963
AL_3	-0.0423	0.0015***	-0.0604	0.0726*	0.0389	0.6717
AL_4	-0.0702	0.0000***	-0.1511	0.0000***	-0.0852	0.3516
VIX	1.9542	0.0223*	8.6821	0.0001***	14.3783	0.0177**
EPU	-0.0631	0.0010***	-0.1348	0.0057***	-0.1315	0.3154
VIX_1	0.3209	0.7168	1.6625	0.4544	3.4736	0.5578
EPU_1	0.0441	0.0226**	0.0441	0.3673	-0.2022	0.1202

Note. Table 7 reports the QARDL estimation results of the effect of EPU and VIX on the illiquidity market during the tranquil period that spans from January 01, 2019, to December 30, 2019. *Significant at 10%; **significant at 5%; ***significant at 1%.

TABLE 8: QARDL estimation results: tranquil period (independent variables: EPU and IDEMV).

Quantile (τ)	0.25		0.50		0.75	
Variables	Coeff	Pr ($> t $)	Coeff	Pr ($> t $)	Coeff	Pr ($> t $)
Short run						
Const	-1.2465	0.3125	15.8573	0.1255	31.3590	0.1686
AL_1	-0.9920	0.000***	-0.9466	0.000***	-0.8889	0.000***
IDEMV	0.0114	0.9799	-4.6207	0.2254	-3.1316	0.7088
EPU	-0.0373	0.0000**	-0.2005	0.0041**	-0.1317	0.3895
IDEMV_1	0.7716	0.0887*	5.7665	0.1287	0.2072	0.9802
EPU_1	0.0080	0.3614	0.0534	0.4654	0.0250	0.8766
IDEMV_2	-0.4782	0.2894	-4.8139	0.2032	-7.3407	0.3779
EPU_2	0.0146	0.0995*	0.0767	0.2996	0.1812	0.2659
IDEMV_3	1.0915	0.0198**	4.6155	0.2383	-5.0094	0.5608
EPU_3	0.0222	0.0123**	0.0823	0.2664	0.1750	0.2833
IDEMV_4	2.7081	0.000***	10.6161	0.0071**	6.5695	0.4475
EPU_4	0.0083	0.3208	0.0184**	0.7929	0.1709	0.2687
Long run						
IDEMV	0.0115	0.9799	-4.8813	0.2237	-3.5231	0.7081
EPU	-0.0376**	0.0000***	-0.2118	0.0044***	-0.1481	0.3929
IDEMV_1	0.7778	0.0879*	6.0919	0.1303	0.2331	0.9802
EPU_1	0.0080***	0.3609	0.0564	0.4664	0.0281	0.8766
IDEMV_2	-0.4820	0.2888	-5.0855	0.2046	-8.2584	0.3822
EPU_2	0.0147**	0.0986*	0.0811	0.2997	0.2039	0.2696
IDEMV_3	1.1003	0.0194**	4.8759	0.2404	-5.6356	0.5593
EPU_3	0.0224**	0.0117*	0.0870	0.2636	0.1968	0.2802
IDEMV_4	2.7299	0.000***	11.2151	0.0075***	7.3907	0.4496
EPU_4	0.0084	0.3199	0.0194	0.7925	0.1922	0.2659

Note. Table 8 reports the QARDL estimation results of the effect of EPU and IDEMV on the illiquidity market during the tranquil period that spans from January 01, 2019, to December 30, 2019. *Significant at 10%; **significant at 5%; ***significant at 1%.

short term, a 1% increase in EPU_1, respectively, leads to an increase in AL in the first quantile (3%), the second quantile (21%), and the third quantile (49%). Similarly, in the long run, a 1% increase in EPU_1 leads to an increase in AL of 4% in the first quantile, 29% in the second quantile, and 85% in the third quantile, respectively. In addition, Table 10

presents the results of the estimation of the link between VIX and illiquidity. This table shows that the current VIX is positively significant at the 1% significance level for both the long term and short term in all quantiles. A 1% increase in VIX increases AL by 656%, 1750%, and 2697% in the short term and by 746%, 2029%, and 3050% in the long term. This

TABLE 9: QARDL estimation results: pandemic period (independent variable: EPU).

Quantile (τ)	0.25		0.50		0.75	
	Coeff	Pr ($> t $)	Coeff	Pr ($> t $)	Coeff	Pr ($> t $)
Short run						
Const	3.1772	0.4107	12.5942	0.3070	43.4451	0.0305**
AL_1	-0.8872	0.0000***	-0.7102	0.0000***	-0.5770	0.0000***
AL_2	-0.0137	0.1727	-0.0030	0.9253	0.1832	0.0005***
AL_3	-0.0239	0.0155**	-0.0586	0.0629*	-0.1182	0.0211**
AL_4	-0.0327	0.0008***	-0.0109	0.7253	0.1859	0.0002***
EPU	-0.0150	0.3569	-0.1049	0.0444**	-0.3025	0.0004***
EPU_1	0.0387	0.0153**	0.2112	0.0000***	0.4938	0.0000***
Long run						
AL_2.1	-0.0155	0.1738	-0.0042	0.9253	0.3175	0.0002***
AL_3.1	-0.0270	0.0152**	-0.0825	0.0638	-0.2049	0.0242**
AL_4.1	-0.0368	0.0008***	-0.0153	0.7256	0.3221	0.0003***
EPU.1	-0.0169	0.3557	-0.1478	0.0423**	-0.5242	0.0004***
EPU_1.1	0.0436	0.0146**	0.2975	0.0000***	0.8557	0.0000***

Note. Table 9 reports the QARDL estimation results of the effect of EPU on the illiquidity market during the pandemic period that spans from December 31, 2019, to December 31, 2020. *Significant at 10%; **significant at 5%; ***significant at 1%.

TABLE 10: QARDL estimation results: pandemic period (independent variable: VIX).

Quantile (τ)	0.25		0.50		0.75	
Variables	Coeff	Pr ($> t $)	Coeff	Pr ($> t $)	Coeff	Pr ($> t $)
Short run						
Const	0.0000	1.0000	-63.9677	0.0000***	-99.6605	0.0000***
AL_1	-0.8789	0.0000***	-0.8620	0.0000***	-0.8851	0.0000***
VIX	6.5618	0.0000***	17.4952	0.0000***	26.9971	0.0000***
VIX_1	0.6543	0.6841	-2.8567	0.2789	1.5695	0.6480
VIX_2	-7.2161	0.0000***	-3.6110	0.1460	-20.7887	0.0000***
VIX_3	0.0000	1.0000	-14.7843	0.0000***	-9.0325	0.0056***
VIX_4	0.0000	1.0000	8.5085	0.0000***	11.1100	0.0000***
Long run						
VIX	7.4658	0.0000***	20.2956	0.0000***	30.5008	0.0000***
VIX_1	0.7444	0.6827	-3.3140	0.2870	1.7732	0.6448
VIX_2	-8.2102	0.0000***	-4.1890	0.1456	-23.4867	0.0000***
VIX_3	0.0000	1.0000	-17.1508	0.0000***	-10.2047	0.0048***
VIX_4	0.0000	1.0000	9.8705	0.0000***	12.5518	0.0000***

Note. Table 10 reports the QARDL estimation results of the effect of VIX on the illiquidity market during the pandemic period that spans from December 31, 2019, to December 31, 2020. *Significant at 10%; **significant at 5%; ***significant at 1%.

means that investor fear (as measured by the VIX) leads to an increase in the magnitude of illiquidity as τ moves to higher quantiles. Second, the lagged VIX has significant explanatory power for illiquidity in both the long run and short run. At lags 2 (ρ_1 and ρ_3) and 3 (ρ_2 and ρ_3), the effect is negative.

Let us now look at the impact of the IDEMV on liquidity. Table 11 reveals that the current IDEMV is negatively significant in both the short run and long run at the 1% significance level for all quantiles. Thus, a 1% increase in the IDEMV reduces AL by 77%, 177%, and 346% in the short run and by 78%, 226%, and 466% in the long run. Consistent with the EPU estimates, the IDEMV is significant and positive in lags 1 to 3 for all quantiles, except in lag 2 where it is significant in the first quantile. The analysis of the immediate effects of the EPU and the VIX on illiquidity is presented in Table 12. The current VIX has a positive and significant impact on illiquidity in all quantiles. In the short term, a 1% increase in the VIX increases AL by 308%, 2241%, and 2518%.

Similarly, a 1% increase in the VIX in the long run increases AL by 333%, 2411%, and 2431%. Conversely, the EPU is negatively significant in the short and long run at the 1% significance level for all quantiles. A 1% increase in EPU decreases AL by 8.4%, 31%, and 47% in the short term and by 9%, 33%, and 45% in the long term. For the previous effect, the VIX appears positive and significant at lag 1 (quantiles ρ_1 and ρ_3) and lag 4 (ρ_2 and ρ_3). A negative and significant effect is observed at lag 2 (all quantiles) and lag 3 (quantile ρ_3) in the short term and long term.

Likewise, in the short run and long run, EPUs have a positive and significant impact in lags 1 (quantiles ρ_2 and ρ_3) and 3 (quantile ρ_1) and a negative and significant impact in lag 4 at quantile 3. We now focus on the combined effects of the EPU and IDEMV on illiquidity. Table 13 shows that the current IDEMV is negatively significant at the 1% and 5% significance levels in both the short run and long run for all quantiles. A 1% increase in the IDEMV decreases AL by 65%, 123%, and 197% in the short run and by 67%, 148%,

TABLE 11: QARDL estimation results: pandemic period (independent variable: IDEMV).

Quantile (τ)	0.25		0.50		0.75	
Variables	Coeff	Pr ($> t $)	Coeff	Pr ($> t $)	Coeff	Pr ($> t $)
Short run						
Const	4.0073	0.3767	2.4747	0.7833	56.9443	0.0000***
AL_1	-0.9817	0.0000***	-0.7820	0.0000***	-0.7429	0.0000***
AL_2	-0.0245	0.1067	0.0038	0.8989	0.0784	0.0713*
AL_3	-0.0311	0.0415**	-0.0545	0.0717*	-0.0889	0.0414**
AL_4	-0.0499	0.0010***	0.0083	0.7803	0.1203	0.0054***
IDEMV	-0.7733	0.0001***	-1.7751	0.0000***	-3.4640	0.0000***
IDEMV_1	0.6116	0.0035***	2.4019	0.0000***	4.0713	0.0000***
IDEMV_2	0.8150	0.0002***	0.2587	0.5477	0.1780	0.7739
IDEMV_3	0.5957	0.0058***	1.9761	0.0000***	2.6656	0.0000***
IDEMV_4	0.1140	0.5696	-0.2982	0.4541	-0.5025	0.3812
Long run						
AL_2	-0.0250	0.1076	0.0049	0.8987	0.1055	0.0663
AL_3	-0.0316	0.0411**	-0.0696	0.0721*	-0.1197	0.0428**
AL_4	-0.0509	0.0010***	0.0107	0.7799	0.1619	0.0051***
IDEMV	-0.7877	0.0001***	-2.2699	0.0000***	-4.6626	0.0000***
IDEMV_1	0.6230	0.0035***	3.0713	0.0000***	5.4802	0.0000***
IDEMV_2	0.8302	0.0001***	0.3308	0.5449	0.2396	0.7728
IDEMV_3	0.6069	0.0055***	2.5269	0.0000***	3.5881	0.0000***
IDEMV_4	0.1162	0.5687	-0.3813	0.4558	-0.6764	0.3850

Note. Table 11 reports the QARDL estimation results of the effect of IDEMV on the illiquidity market during the pandemic period that spans from December 31, 2019, to December 31, 2020. *Significant at 10%; **significant at 5%; ***significant at 1%.

TABLE 12: QARDL estimation results: pandemic period (independent variables: EPU and VIX).

Quantile (τ)	0.25		0.50		0.75	
Variables	Coeff	Pr ($> t $)	Coeff	Pr ($> t $)	Coeff	Pr ($> t $)
Short run						
Const	-8.4561	0.1402	-95.0835	0.0000***	-98.2765	0.0000***
AL_1	-0.9272	0.0000***	-0.9293	0.0000***	-1.0359	0.0000***
AL_2	-0.0361	0.0109**	0.0015	0.9715	0.0133	0.7967
AL_3	-0.0439	0.0020***	-0.1693	0.0001***	-0.1450	0.0052***
AL_4	-0.0476	0.0007***	-0.1740	0.0000***	-0.1213	0.0178
VIX	3.0882	0.0000***	22.4112	0.0000***	25.1829	0.0000***
EPU	-0.0840	0.0002***	-0.3139	0.0000***	-0.4757	0.0000***
VIX_1	1.6703	0.0763*	-3.6870	0.1948	5.6904	0.0997*
EPU_1	0.0005	0.9839	0.0944*	0.1749	0.0306**	0.7170
VIX_2	-3.2409	0.0006***	-14.1663	0.0000***	-22.3818	0.0000***
EPU_2	0.0024	0.9185	-0.0245	0.7270	-0.0201	0.8136
VIX_3	0.9597	0.2976	-3.8523	0.1667	-5.8240	0.0853*
EPU_3	0.0742	0.0011***	0.0313	0.6476	0.1244	0.1350
VIX_4	-1.1686	0.1253	10.2450	0.0000***	14.2480	0.0000***
EPU_4	0.0037	0.8561	-0.0781	0.2091	-0.1733	0.0221**
Long run						
AL_2	-0.0389	0.0106**	0.0016***	0.9715	0.0129	0.7965
AL_3	-0.0473	0.0018***	-0.1821	0.0001***	-0.1400	0.0050***
AL_4	-0.0513	0.0006***	-0.1872	0.0000***	-0.1171	0.0162
VIX	3.3305	0.0000***	24.1163	0.0000***	24.3101	0.0000***
EPU	-0.0906	0.0001***	-0.3377	0.0000***	-0.4592	0.0000***
VIX_1	1.8014	0.0724*	-3.9675	0.2050	5.4932	0.0890*
EPU_1	0.0005	0.9839	0.1016	0.1782	0.0295	0.7175
VIX_2	-3.4951	0.0005***	-15.2441	0.0000***	-21.6061	0.0000***
EPU_2	0.0026	0.9184	-0.0263	0.7272	-0.0194	0.8137
VIX_3	1.0349	0.2980	-4.1454	0.1629	-5.6222	0.0819*
EPU_3	0.0800	0.0011***	0.0337	0.6477	0.1200	0.1363
VIX_4	-1.2603	0.1242	11.0244	0.0000***	13.7542	0.0000***
EPU_4	0.0040	0.8560	-0.0840	0.2122	-0.1673	0.0242**

Note. Table 12 reports the QARDL estimation results of the effect of EPU and VIX on the illiquidity market during the pandemic period that spans from December 31, 2019, to December 31, 2020. *Significant at 10%; **significant at 5%; ***significant at 1%.

TABLE 13: QARDL estimation results: pandemic period (independent variables: EPU and IDEMV).

Quantile (τ)	0.25		0.50		0.75	
Variables	Coeff	Pr ($> t $)	Coeff	Pr ($> t $)	Coeff	Pr ($> t $)
Short run						
Const	2.4325	0.6334	21.3042	0.1341	90.3051	0.0001***
AL_1	-0.9796	0.0000***	-0.8353	0.0000***	-0.8095	0.0000***
IDEMV	-0.6585	0.0010***	-1.2387	0.0254**	-1.9756	0.0243**
EPU	-0.0553	0.0381**	-0.1172	0.1141	-0.1849	0.1153
IDEMV_1	0.6359	0.0027***	2.6766	0.0000***	4.0234	0.0000***
EPU_1	-0.0352	0.1917	-0.0148	0.8434	-0.0200	0.8658
IDEMV_2	0.6870	0.0017***	0.3781	0.5324	1.9227	0.0455**
EPU_2	-0.0312	0.2481	0.0418	0.5778	-0.0963	0.4179
IDEMV_3	0.6953	0.0012***	2.3078	0.0001***	3.1941	0.0007***
EPU_3	0.0744	0.0058***	0.0386	0.6057	0.0700	0.5546
IDEMV_4	-0.0427	0.8341	0.2149	0.7049	0.7494	0.4043
EPU_4	0.0064	0.8046	-0.1121	0.1189	-0.1503	0.1861
Long run						
IDEMV	-0.6722	0.0009***	-1.4830	0.0267**	-2.4404	0.0277**
EPU	-0.0565	0.0365**	-0.1403	0.1094	-0.2284	0.1092
IDEMV_1	0.6492	0.0027***	3.2046	0.0000***	4.9700	0.0001***
EPU_1	-0.0359	0.1908	-0.0177	0.8433	-0.0248	0.8656
IDEMV_2	0.7013	0.0014***	0.4527	0.5290	2.3751	0.0386**
EPU_2	-0.0318	0.2472	0.0500	0.5778	-0.1190	0.4175
IDEMV_3	0.7098	0.0010***	2.7629	0.0001***	3.9457	0.0006***
EPU_3	0.0760	0.0057***	0.0462	0.6060	0.0864	0.5557
IDEMV_4	-0.0436	0.8341	0.2573	0.7035	0.9257	0.3972
EPU_4	0.0065	0.8045	-0.1342	0.1187	-0.1857	0.1870

Note. Table 12 reports the QARDL estimation results of the effect of EPU and IDEMV on the illiquidity market during the pandemic period that spans from December 31, 2019, to December 31, 2020. *Significant at 10%; **significant at 5%; ***significant at 1%.

and 244% in the long run. Furthermore, the current EPU is negatively significant in both the short term and long term at the 1% significance level only for the first quantile. A 1% increase in the EPU decreases AL by 5% in both the short term and long term. For the lagged impact, IDEMV is positively significant at lag 1 for all quantiles, at lag 2 for quantiles ρ_1 and ρ_3 , and at lag 3 for all quantiles. Similarly, for the EPU, a positive and significant effect is observed at lag 2 (quantiles ρ_1 and ρ_3) and lag 3 (quantile ρ_1) in both short and long periods.

3.2. Wavelet Coherence Results. We try to use both bivariate and multiple wavelets. Our main objective is to assess the co-movement and dynamic correlation between the variables in the time-scale space and over the tranquil and pandemic periods. Figure 1 reports the coherency between illiquidity and EPU over the tranquil sample period and across different scales. From the plot, we detect that the phase difference as revealed by the arrows differs across time and frequency domains suggesting that there is no joint periodicity in the couple. Likewise, in the short scales, the coherency plot does spread inconsistently throughout the data span where it is rather dispersed, and the phase difference as indicated by the arrows are non-homogenous. We exhibit small coherency contours where arrows showing left, right, up, and down are scattered over the short run. Also, a visual look into this plot shows that the highest level of coherency ranging between 0.8 and 0.9 is perceived in the long horizon corresponding to 64–128 days of scales and over the period

starting from April 2020 and ending in September 2020. The arrows are showing right and down indicating thus the leading effect of the EPU in high scales. This finding corroborates those of the QARDL model. More precisely, we exhibit a strong relationship between EPU and illiquidity inclined to the US market and highly changing from short to long run. This implies that increased economic policy uncertainty is associated with a stock market liquidity downturn.

The co-movement between implied volatility and illiquidity is revealed in Figure 2. Significant coherencies are scattered both in short and long horizons; however, we observe noticeable energy concentrations ranging from 0.9 to 1 and occurring from the medium to high scales, suggesting long-term relationships between implied volatility and illiquidity. Overall, in low frequency levels (i.e., high scales), the arrows' direction to the right and down recognizes the positive and leading effects of VIX on illiquidity. The combined effect of EPU and VIX on US stock market liquidity is exhibited in Figure 3. Notably, a significant joined effect of EPU and VIX on US liquidity is revealed across scales and over time. However, while red small areas are scattered over short scales, the strongest regions of combined impact are localized in the high scales indicating by this way the long-term effects on liquidity. These findings are similar to our previous result generated by the QARDL model. The co-movement between liquidity and IDEMV is plotted in Figure 4. The coherency is mainly revealed over the period April 2020 to October 2020 across the medium to long-term scales. A negative relationship is mostly localized

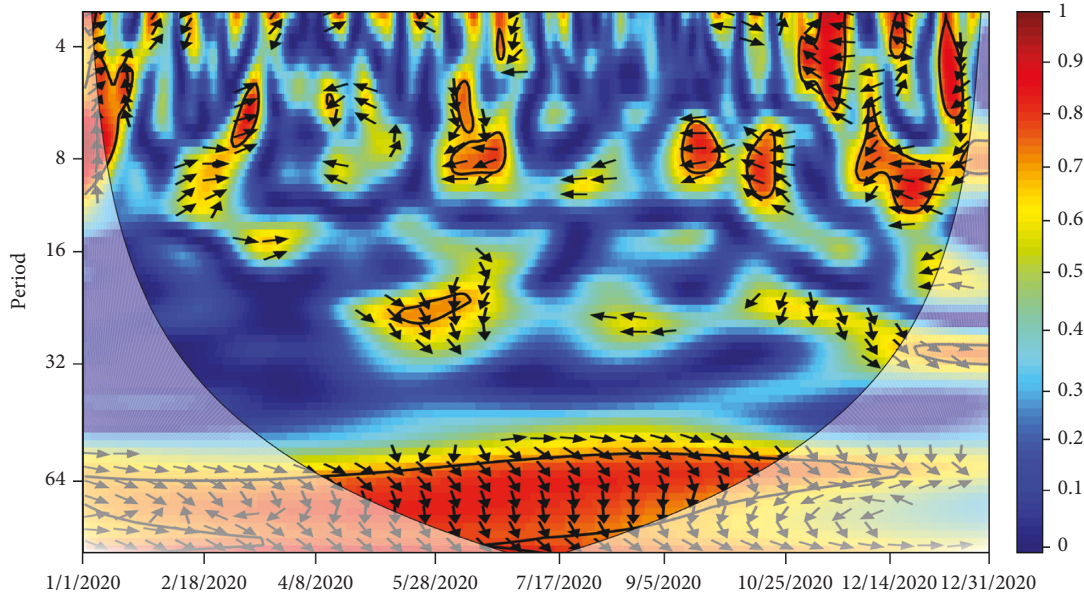


FIGURE 1: Wavelet coherence between illiquidity and EPU (tranquil period). Note: this figure reports the wavelet coherence between illiquidity and EPU during tranquil period. The black contour represents the regions in which the spectrum is significant at the 5% level against red noise. The cone of influence denoted as COI is designated by the lighter shade which delineates the high power regions. Time and scale (days) are represented on the horizontal and vertical axes, respectively. Arrows pointed to the right (resp. left) signify that the variables are in phase (out of phase). If arrows move to the right and up (resp. down), the first variable is the driver (resp. follower). By contrast, if arrows move to the left and up (down), the second variable is leading (resp. lagging).

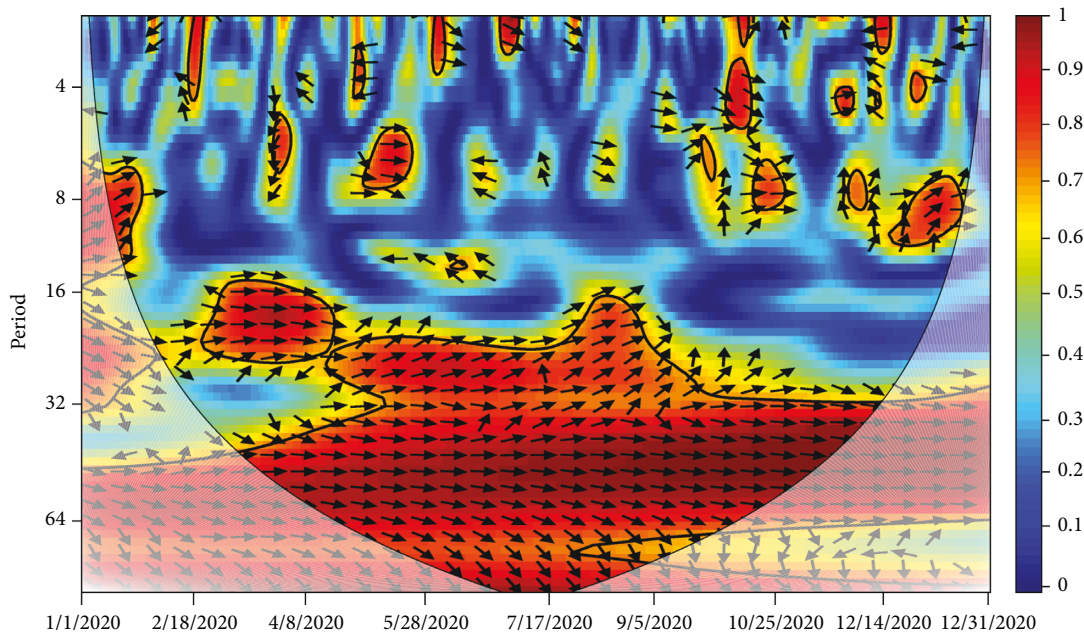


FIGURE 2: Illiquidity vs. VIX wavelet coherence (tranquil period). Note: this figure reports the wavelet coherence between illiquidity and VIX during tranquil period. The black contour represents the regions in which the spectrum is significant at the 5% level against red noise. The cone of influence denoted as COI is designated by the lighter shade which delineates the high power regions. Time and scale (days) are represented on the horizontal and vertical axes, respectively. Arrows pointed to the right (resp. left) signify that the variables are in phase (out of phase). If arrows move to the right and up (resp. down), the first variable is the driver (resp. follower). By contrast, if arrows move to the left and up (down), the second variable is leading (resp. lagging).

in the long term (the arrows are left and downward indicating an anti-phase relationship). While the phase difference of IDEMV and liquidity couple is inconclusive over the

tranquil period, the inclusion of EPU to assess the joint effect of these indices on liquidity (see Figure 5) is remarkably pronounced. More explicitly, high combined effect of

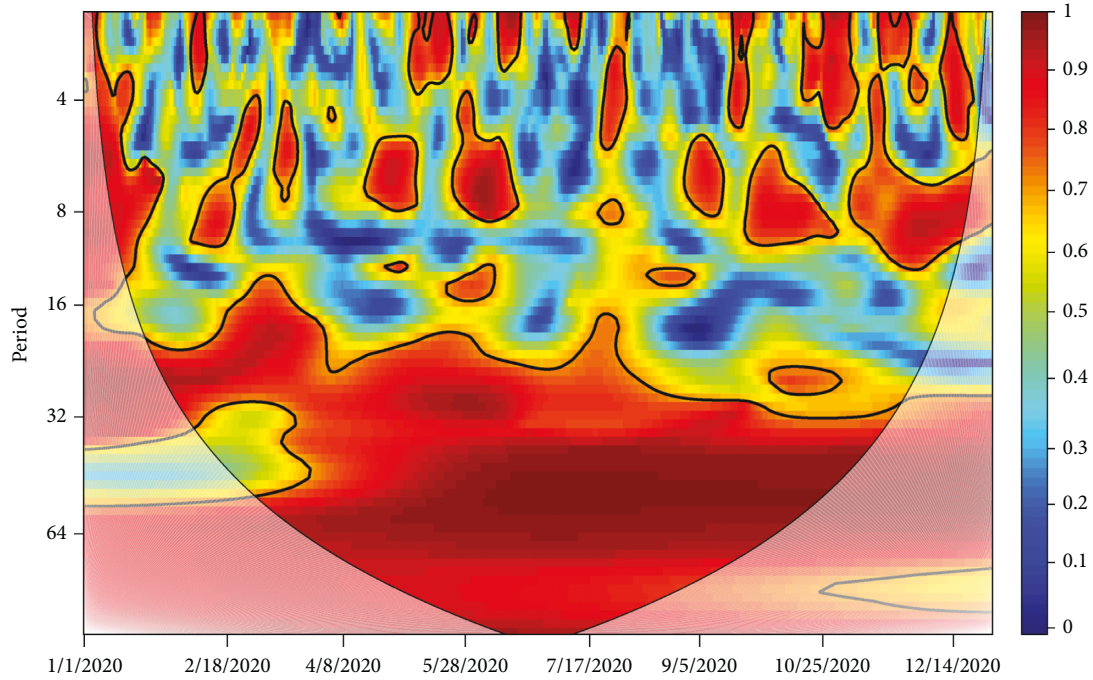


FIGURE 3: The combined effect of EPU and VIX on illiquidity (tranquil period). Note: this figure represents the combined effect of between EPU and VIX on US illiquidity during tranquil period. The black contour represents the regions in which the spectrum is significant at the 5% level against red noise. The cone of influence denoted as COI is designated by the lighter shade which delineates the high power regions. Time and scale (days) are represented on the horizontal and vertical axes, respectively. Arrows pointed to the right (resp. left) signify that the variables are in phase (out of phase). If arrows move to the right and up (resp. down), the first variable is the driver (resp. follower). By contrast, if arrows move to the left and up (down), the second variable is leading (resp. lagging).

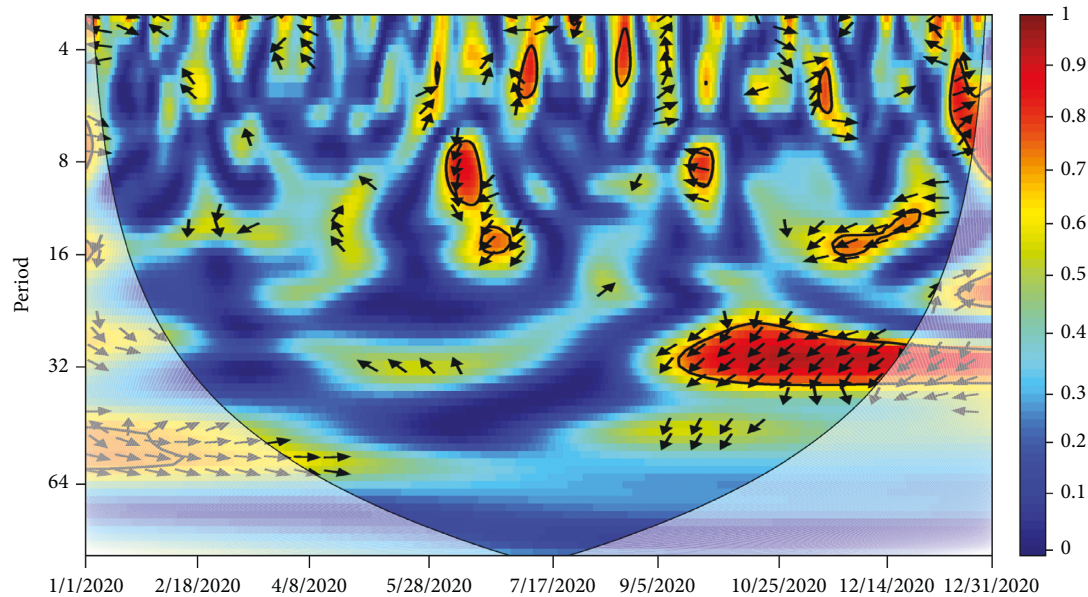


FIGURE 4: The wavelet coherence between illiquidity and IDEMV (tranquil period). Note: this figure reports the wavelet coherence between illiquidity and IDEMV during tranquil period. The black contour represents the regions in which the spectrum is significant at the 5% level against red noise. The cone of influence denoted as COI is designated by the lighter shade which delineates the high power regions. Time and scale (days) are represented on the horizontal and vertical axes, respectively. Arrows pointed to the right (resp. left) signify that the variables are in phase (out of phase). If arrows move to the right and up (resp. down), the first variable is the driver (resp. follower). By contrast, if arrows move to the left and up (down), the second variable is leading (resp. lagging).

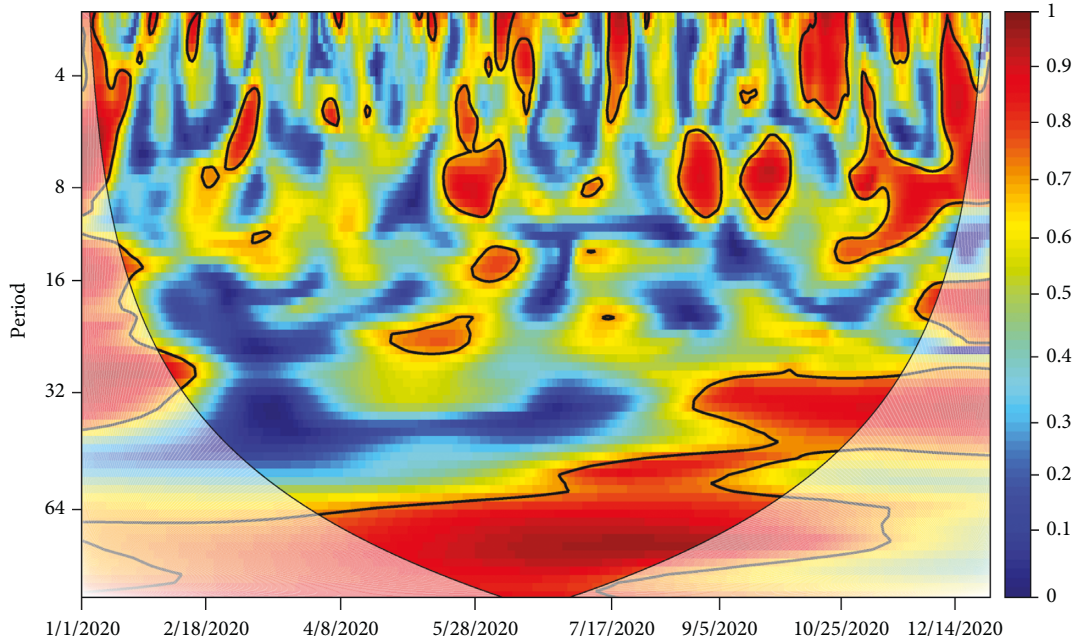


FIGURE 5: The combined effects of EPU and IDEMV on illiquidity (tranquil period). Note: this figure reports the combined effect of EPU and IDEMV on illiquidity during tranquil period. The black contour represents the regions in which the spectrum is significant at the 5% level against red noise. The cone of influence denoted as COI is designated by the lighter shade which delineates the high power regions. Time and scale (days) are represented on the horizontal and vertical axes, respectively. Arrows pointed to the right (resp. left) signify that the variables are in phase (out of phase). If arrows move to the right and up (resp. down), the first variable is the driver (resp. follower). By contrast, if arrows move to the left and up (down), the second variable is leading (resp. lagging).

IDEMV and EPU on US liquidity is dispersed over time and especially across low and high frequency (i.e., short and long horizons). As exhibited from the QARDL outputs, the IDEMV explanatory power on liquidity is improved when it is combined with EPU.

During pandemic period, the co-movement between EPU and liquidity (Figure 6) is visible over different scales (short, medium, and long horizons). Arrows are heterogeneous and they changed direction from a horizon to another. While they are right-up in the short run, they are pointed to right and down in the long run. Overall, this is a positive relationship between the variables (in-phase relationship). From the plot, compared to the co-movement between EPU and liquidity over the tranquil period, we easily understand that EPU effect is more interesting in the pandemic period. Figure 7 reports the co-movement between illiquidity and VIX. Overall, regardless the arrow direction, it is worth to note that there is a positive and significant coherency between illiquidity and VIX index over the sample period and across all frequencies. In low scales corresponding to (2–4) and (4–8), the arrows are pointed to the right and up indicating that illiquidity causes increases in US implied volatility. However, VIX is leading the US illiquidity in the medium and high scales (i.e., medium and long-term horizons) in the middle of the sample period (May 2020–September 2020). This finding allows to show the significant explanatory power of VIX on US illiquidity.

The leading role of IDEMV on US illiquidity over the pandemic period is exhibited in the long term (see Figure 8). For this couple, a positive and significant coherency is

remarkably shown over the sample period and mainly localized in low scales. A visual inspection to the combined effects of EPU and VIX on US illiquidity (Figure 9) permits to recognize main findings. First, during the pandemic period, strong combined impacts of both EPU and VIX on illiquidity are scattered over the sample period and across all scales. Second, it is worth noting that the strength of the combined coherency for EPU and VIX is higher compared to those joint effects during tranquil period. Furthermore, we perceive a strong combined effect of EPU and IDEMV on the illiquidity (Figure 10). This effect is visualized over the whole sample period and especially spread in long horizon. These findings corroborate those generated by the QARDL model.

4. Discussion and Implications

Academics and market participants agree that during the current COVID-19 pandemic period, uncertainty about the stability of the stock market in the short term and long term has increased, which may have a clear impact on the optimal portfolio equilibrium. As discussed above, many authors have examined the link between the COVID-19 epidemic and stock markets. They have indicated that this outbreak had a significant effect on financial markets. Similarly, this study explores the explanatory power of uncertainty indices on the illiquidity of the US financial market in tranquil and pandemic periods. For this reason, the QARDL and wavelet coherence approaches were considered to investigate the impact of the EPU, VIX, and IDEMV on illiquidity across

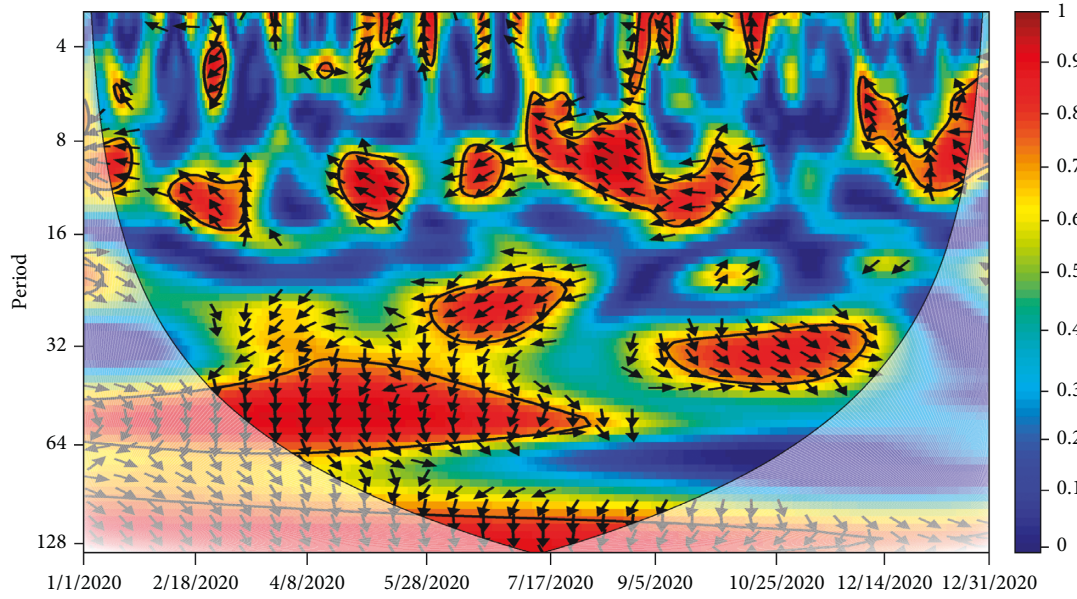


FIGURE 6: The wavelet coherence between illiquidity and EPU (pandemic period). Note: this figure reports the wavelet coherence between illiquidity and EPU during pandemic period. The black contour represents the regions in which the spectrum is significant at the 5% level against red noise. The cone of influence denoted as COI is designated by the lighter shade which delineates the high power regions. Time and scale (days) are represented on the horizontal and vertical axes, respectively. Arrows pointed to the right (resp. left) signify that the variables are in phase (out of phase). If arrows move to the right and up (resp. down), the first variable is the driver (resp. follower). By contrast, if arrows move to the left and up (down), the second variable is leading (resp. lagging).

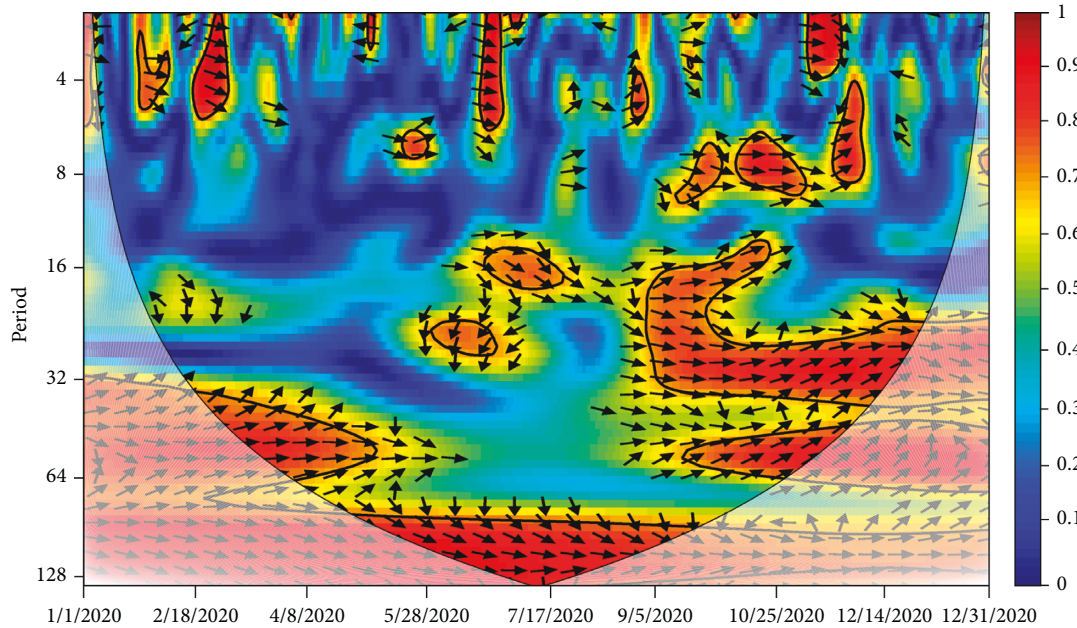


FIGURE 7: The wavelet coherence between illiquidity and VIX (pandemic period). Note: this figure reports the wavelet coherence between illiquidity and VIX during pandemic period. The black contour represents the regions in which the spectrum is significant at the 5% level against red noise. The cone of influence denoted as COI is designated by the lighter shade which delineates the high power regions. Time and scale (days) are represented on the horizontal and vertical axes, respectively. Arrows pointed to the right (resp. left) signify that the variables are in phase (out of phase). If arrows move to the right and up (resp. down), the first variable is the driver (resp. follower). By contrast, if arrows move to the left and up (down), the second variable is leading (resp. lagging).

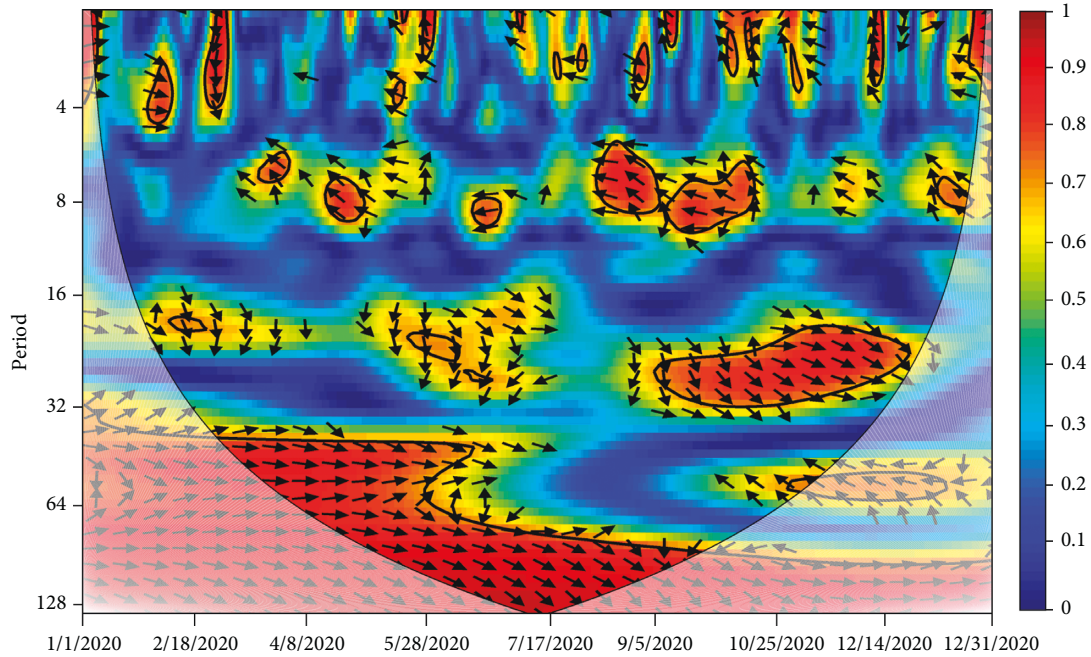


FIGURE 8: The wavelet coherency between illiquidity and IDEMV (pandemic period). Note: this figure reports the wavelet coherency between illiquidity and IDEMV during pandemic period. The black contour represents the regions in which the spectrum is significant at the 5% level against red noise. The cone of influence denoted as COI is designated by the lighter shade which delineates the high power regions. Time and scale (days) are represented on the horizontal and vertical axes, respectively. Arrows pointed to the right (resp. left) signify that the variables are in phase (out of phase). If arrows move to the right and up (resp. down), the first variable is the driver (resp. follower). By contrast, if arrows move to the left and up (down), the second variable is leading (resp. lagging).

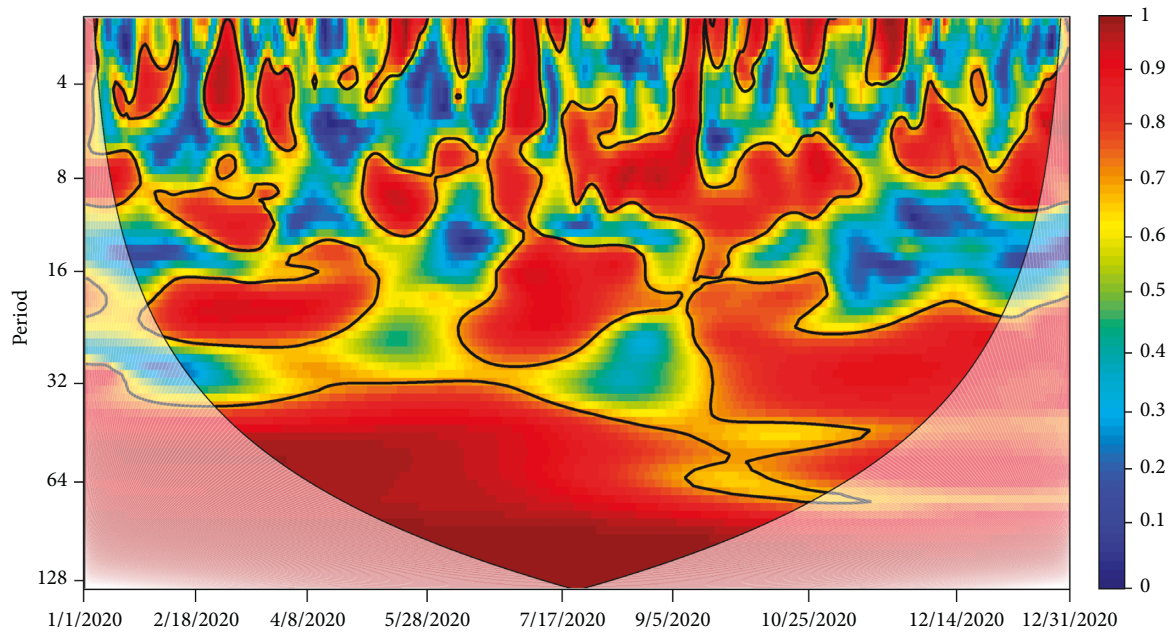


FIGURE 9: The combined effects of EPU and VIX on illiquidity (pandemic period). Note: this figure reports the combined effects of EPU and VIX on illiquidity during pandemic period. The black contour represents the regions in which the spectrum is significant at the 5% level against red noise. The cone of influence denoted as COI is designated by the lighter shade which delineates the high power regions. Time and scale (days) are represented on the horizontal and vertical axes, respectively. Arrows pointed to the right (resp. left) signify that the variables are in phase (out of phase). If arrows move to the right and up (resp. down), the first variable is the driver (resp. follower). By contrast, if arrows move to the left and up (down), the second variable is leading (resp. lagging).

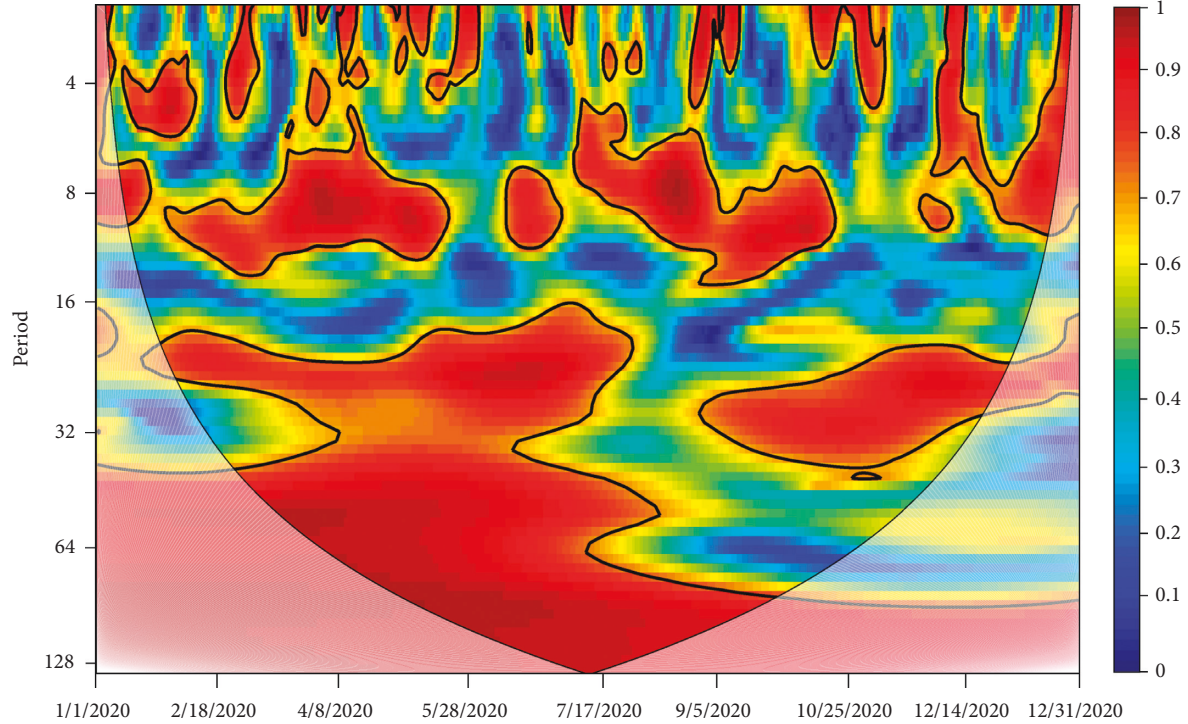


FIGURE 10: The combined effects of EPU and IDEMV on illiquidity (pandemic period). Note: this figure represents the combined effects of EPU and IDEMV on illiquidity during pandemic period. The black contour represents the regions in which the spectrum is significant at the 5% level against red noise. The cone of influence denoted as COI is designated by the lighter shade which delineates the high power regions. Time and scale (days) are represented on the horizontal and vertical axes, respectively. Arrows pointed to the right (resp. left) signify that the variables are in phase (out of phase). If arrows move to the right and up (resp. down), the first variable is the driver (resp. follower). By contrast, if arrows move to the left and up (down), the second variable is leading (resp. lagging).

frequencies and over time. The QARDL results reveal a significant and negative error correction parameter for all quantiles. This means a very fast transition from short-term to long-term equilibrium between the uncertainty variables and illiquidity.

Furthermore, the QARDL results prove that, in calm periods, uncertainty measured by the lagged EPU, the current VIX, and the lagged VIX contributes to the decrease in liquidity of the US stock market. These results confirm those of the wavelet approach which showed significant effects of the EPU and the VIX in terms of decreasing liquidity in the short term and long term. However, there is an improvement in liquidity when considering the current EPU as an explanatory variable. This is in line with Sayed and Bouri [30] who showed a significant spillover effect of global economic policy uncertainty (GEPU) on the financial markets of oil exporters and importers in developed and emerging economies.

Compared to the tranquil period, the QARDL results show that the explanatory power of the EPU and VIX coefficients increases during the pandemic period. Negative and significant effects of the current EPU and lagged VIX increase liquidity, while positive and significant effects of the lagged EPU and current VIX decrease liquidity in the US stock market in the short run and long run. This confirms the results of Bouri et al. [28] and Dutta et al. [32] on the importance of US implied volatility. The later finding is also

revealed by the wavelet tool. Overall, the EPU becomes more powerful when the pandemic period is taken into account. Evidence shows that all coefficients measuring the instantaneous and lagged EPU increase in an interesting way.

In financial terms, this leads to two contrasting cases. When the amount of information about policy uncertainty arrives in the US financial market instantaneously, it makes the level of liquidity high. This can be explained by investors' fear regarding the instability of the market during the COVID-19 pandemic, which will force them to quickly adopt an investment strategy by selling or buying securities. However, when EPU information flows into the market with a time lag, it reduces liquidity considerably. This means that the arrival of EPU information can reduce liquidity because investors may be afraid of the continuity of uncertainty over time, and they change their investment strategy by reducing trading.

With regard to the effects of the VIX during the pandemic period, the information content of the lagged VIX appears to have some persistence in improving short-term and long-term liquidity during the coronavirus crisis, while, contemporaneously, the role of the US fear shock among investors leads to the evaporation of liquidity. In more detail, with the passage of time, this risk caused by the US fear shock has lost its detrimental effect on liquidity and its role has become positive and liquidity has improved. This suggests that investors are coping with the fear resulting from

the COVID-19 crisis with every experience and efficiency, after it affected them negatively when it happened instantaneously.

As in the case of the UPR, the pandemic US VIX dominates the tranquil US VIX. The results show that all estimated coefficients increase. This highlights that the US VIX is more sensitive to the pandemic period than to the tranquil period, which means that the COVID-19 outbreak worsens the liquidity situation, especially contemporaneously. On the other hand, the information content of infectious diseases (as measured by the IDEMV) has no effect on liquidity during the calm period. This confirms the results achieved by the wavelet approach. Furthermore, the uncertainty caused by the effect of the infectious disease on the financial market during the pandemic crisis seems to play an important role in the improvement of liquidity on an instantaneous basis, whereas it was not significant during the tranquil period. This corroborates the results revealed by Bouri et al. [31] that the role of the IDEMV index is important in terms of prediction during the COVID-19 pandemic. The information flow generated by the infectious disease in the financial market forces investors to quickly adopt a long-short investment strategy and thus improves liquidity. However, positive lags mean reduced liquidity since investors are frightened by the continuing impact of the pandemic on the US financial market, forcing them to reduce speculative trading. It may also mean an evaporation of liquidity.

Furthermore, the test of the combined effect of the EPU and the VIX reveals that the uncertainty arising from implied volatility decreases liquidity in a lagged and contemporaneous manner, while an improvement in liquidity is found in the case of the EPU. This result corroborates those proven by the wavelet tool which illustrates that the significant combined effect between the VIX and the EPU is located in the high scales suggesting the potential for an increase in liquidity in the US financial market. This result corroborates those proven by the wavelet tool which illustrates that the significant combined effect between the VIX and the EPU is located in the high scales indicating the leading explanatory power of the VIX and the EPU on illiquidity.

Nevertheless, the information content of both contemporary and lagged economic policy uncertainty generates lower liquidity improvement. However, as shown by the QARDL and wavelet tools, the pandemic crisis further complicates the liquidity situation in the US market. This is especially apparent when we consider the simultaneous effect of the VIX and the UPR. The values of all estimated coefficients are higher than those of the tranquil period. Therefore, as the information flow related to the uncertainty caused by the US fear shock increases, illiquidity increases. In addition, the explanatory power of the EPU is improved. This means that policy-induced uncertainty leads to an increase in liquidity when estimated with the fear index more than when estimated individually. However, this power is still lower than that of the US VIX index, which is considered the main source of reduction in liquidity.

Regarding the simultaneous impact of the UPR and the IDEMV in tranquil times, it is visible that liquidity decreases when considering the lagged and instantaneous IDEMV and increases when considering the EPU index. This conclusion is also supported by the wavelet coherence analysis which indicates that the explanatory power of the IDEMV on illiquidity is improved when considered together with the EPU. However, the QARDL results reveal that, instantaneously, the uncertainty caused by the impact of an infectious disease on the financial market during the pandemic crisis plays a significant role in improving liquidity, whereas it was not significant during the tranquil period. This implies that the arrival of information on the link between infectious diseases and the financial market prompts investors to follow an investment strategy based on long and short positions to boost liquidity.

Yet, the continuous impact over time of the lagged IDEMV reduces liquidity by decreasing trading when considered together with the EPU. In addition, the uncertainty caused by economic policy also leads to an instantaneous improvement in liquidity. However, the opposite is true in the previous way. Overall, we conclude that the permanence of the information flow related to the uncertainty caused by the EPU and the economic policy in the US market place investors in a critical situation that forces them to adopt strategies based on the reduction of trading operations.

Our results have a number of management implications. First, the significant effects of the lagged values of the uncertainty indices can be taken into account by US financial market participants in forecasting the current level of liquidity for both the calm and the pandemic periods. Therefore, forecasting liquidity using information contained in implied volatility, economic policy uncertainty, and infectious disease leads investors to better compose their speculative strategies and successfully implement short and long-term hedging instruments. Second, the increase in the explanatory power of implied volatility for illiquidity is more observed during the pandemic period than during the tranquil period. This may be forcing US financial market decision makers to consider the uncertainty caused by investor fear as a significant risk and danger that destabilizes the market and evaporates liquidity. In addition, asset managers appear to have a leading role to play in navigating and guiding the danger in this situation. This is done through effective communication and support by providing both technological leverage to communicate and practical strategic ideas on how to optimally inject more capital into their existing portfolios with a COVID-19 pandemic still in progress.

Third, our research can complement the literature [58] on liquidity by advancing alternative forecasters for liquidity such as the policy uncertainty index and the infectious disease EMV tracker. This can be seen as a rejection of the semi-strong efficiency hypothesis of the US financial market during the COVID-19 pandemic. This confirms the results of Ferreira [59] who showed the inefficiency of the US market [60–63].

Although this study has important results and policy implications not only for investors but also for policymakers, it presents some limitations. First, this research did not include the COVID-19 pandemic as a possible variable in the relationship between uncertainty indices and illiquidity. Second, it also ignored national measures of uncertainty such as the realized volatility in the research question. The empirical evidence of this study can be improved by taking these limitations into account. New interpretable uncertainty variables can also be discovered in future research by extending the time period and using recent methods such as DFA [58, 59].

Data Availability

The data used to support the findings of this study are available from the corresponding author upon request.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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