US banks in the time of COVID-19: fresh insights from the wavelet approach

Saeed Sazzad Jeris¹ · Ridoy Deb Nath¹

Received: 16 June 2020 / Revised: 22 November 2020 / Accepted: 10 February 2021 /
Published online: 28 April 2021
© Eurasia Business and Economics Society 2021

Abstract

This study explores the impact of COVID-19, crude oil price, US economic policy uncertainty, baltic dry index, and the stock market volatility on the US bank indices. This study is conducted based on the daily data ranging from 21st January 2020 to 30th October 2020. The wavelet coherence analysis suggests that rising COVID-19 cases in the US have a strong impact on both bank indices. Also, global COVID-19 cases influence the bank indices, although it is not as strong as US COVID-19 cases. Additionally, we have found that the US economic policy uncertainty and stock market volatility imposed negative and strong effect on the bank indices in this pandemic situation. Moreover, continuous fluctuation of crude oil price makes the US banks volatile throughout the period.

Keywords US bank indices · COVID-19 · VIX · Oil price · Economic policy uncertainty · Baltic dry index

JEL Classification E52 · G01 · G21

1 Introduction

On January 19, 2020, the Coronavirus pandemic (COVID-19) spread to the United States (Holshue et al. 2020). Over 9 million cases of infection and over 235 thousand cases of deaths were reported thereafter, as per the 30th October data of Worldometer (2020). In addition to the health crisis, the pandemic initiated a severe economic downturn in the nation. Economic downturn, caused by the rapid transmission of COVID-19 and the following oil price shock, is supposed to drive the national

✉ Saeed Sazzad Jeris
saeedjeris30@gmail.com

Ridoy Deb Nath
debnathridoy.official@gmail.com

¹ Department of Business Administration, Shahjalal University of Science and Technology, Sylhet, Bangladesh

economy into its next recession. As the pandemic hit hard, the financial markets suffered a great damage. On February 27, Dow Jones Industrial Average (DJIA) witnessed its largest single-day point drop in the history and S&P 500 observed a 4.4% decline (Li 2020). Although significant rises were also observed in association with the government's responses, the records of decline in stock market have been beaten several times since then.

Nevertheless, the five major US banks observed the strongest results in nearly a decade, as trading levels and debt issuance increased amid COVID-19 (Fitch Ratings 2020). Volatility in the US stock market induced an increase in the trading activities, therefore, banks' trading revenues jumped up to a significant scale. Additionally, the increased need for liquidity by corporations to survive in the economic shutdown gave rise to the debt issuance. Fitch Ratings (2020) reveal that Goldman Sachs enjoyed its greatest fixed income, currencies, and commodities trading revenues in the past five years and Bank of America had its strongest-ever equity-trading results. In addition to that, JP Morgan enjoyed a significant increase in the debt underwriting revenues, as it notched its best-ever investment grade debt issuances. However, the blessing of the increased client activity may prove to be momentary. Federal Reserve brought down its Fed funds rate to between 0.00% and 0.25% (Fitch Ratings 2020). Thus, a follow-up drop in short-term and long-term interest rates is supposed to hamper the bank profitability. Moreover, the decline in economic activity may also cause the banks a significant decline in profitability for several months, as Fitch Ratings (2020) reveal. Client activities are also supposed to drop, causing a fall in fee income, as corporate clients continue to pull back from the market. Therefore, the financial impacts of COVID-19 caused US banks to eventually project a downward fashion in profitability.

However, how the US banks may react to the pandemic and how they can survive in the long run by maintaining a healthy profitability margin requires scholarly attention. As the pandemic continues, a lot of factors in the economy are supposed to affect the banks' return. Prior literatures suggest some of these factors that influence bank performance. Ashraf and Shen (2019) studied the relationship between economic policy uncertainty (EPU) and bank loan pricing. They suggest a significant positive relationship between EPU and interest rates of bank loans. Francis et al. (2014) report that EPU increases the cost of loan contract between banks and US firms. A recent study conducted by Karadima and Louri (2020) suggest that EPU positively impacts bank NPLs. Additionally, Bordo et al. (2016) argue that EPU has a significant negative association with credit growth of banks. Another study conducted by Hu and Dong (2019) reveal similar findings. They suggest that banks' credit growth is affected by EPU, but the effect may vary across banks. However, Jin et al. (2019) argued that EPU has a positive association with bank earning opacity. Although the relationship between oil price movements and stock performances is thoroughly addressed in the literature, the relationship between oil and bank performances is not well-addressed. However, Hesse and Poghosyan (2016) conducted a study on oil-price shocks and bank performance and reported a significant relationship between them. Khandelwal et al. (2016) studied the relationship between oil price and financial development. Their findings suggest a strong linkage between oil price and balance sheets of banks. More recently, Al-Khazali et al.

(2017) investigated the relation between oil-price movements and bank NPLs and suggested that oil price movements affect bank stability in oil-exporting countries. Moreover, existing literature suggest that stock market volatility may also impact bank performances. Tan and Floros (2012) suggest that high level of volatility in stock market can lead to high return on equity (ROE). However, Rashid and Ilyas (2018) argue that volatility in stock market has significant negative impacts on return, assets and equity of the banks. Another stream of study reveals that investor sentiment influences the performance of banking sector in a country. Irresberger et al. (2015) argued that banks' stock performance is significantly driven by investors' "irrational market-wide crisis sentiment" and "idiosyncratic crisis sentiment", especially during financial crisis. Another study conducted by Rashid et al. (2014) reveals that investor sentiment influences bank deposit in Malaysia.

Despite the richness in the existing literature, the economic challenges posed by COVID-19 require new insights. Moreover, the importance of scholarly contribution in the finance literature regarding COVID-19 was extensively addressed by Goodell (2020). Although many prior studies address the economic impact of COVID-19 (e.g. Sharif et al. 2020; Jeris and Nath 2020; Zhang et al. 2020), Therefore, this study attempts to add to the literature by unveiling the banking industry condition in the time of COVID-19 pandemic. In this study, we use the Dow Jones US banks index and the S&P 500 banks index to proxy for banking sector performance. We address both the global and US COVID-19 infection cases reported daily to proxy for COVID-19. Additionally, we address the relationship between stock volatility and banking performance. We use the VIX index to represent volatility in US stocks. We use the WTI crude oil prices to analyze the association of oil prices with banking sector performance. Furthermore, we address the relationship between economic activity and bank performance. We use the Baltic Dry Index (BDI) to proxy for economic activity. Lastly, we address how the US EPU may affect the US banking sector performance. For this purpose, we use the popular EPU index developed by Baker et al. (2016). We use the wavelet coherence analysis in our study. Wavelet coherence analysis has been previously used by various scholars in economic research (e.g. Demir et al. 2020; Karabulut et al. 2020; Sharif et al. 2020).

The rest of the paper advances as follows. Section 2 presents the data and methodology. Section 3 discusses the empirical results. Section 4 concludes and discusses the policy implications and future research areas.

2 Data and methodology

2.1 Data and variable description

Daily observations of S&P 500 banks index, Dow Jones US banks index, both global and US COVID-19 reported cases, WTI crude oil prices, US economic policy uncertainty, VIX US stock volatility and Baltic Dry Index are used in this study. The data ranges from January 21, 2020 to October 30, 2020. We select our sample period based on the data availability of all the variables. Data were collected from Thompson Reuters database. Table 1 presents the data and variables' description.

Table 1 Variables used in this study

Variable/s	Proxy	Proxy name
US Banks Performance	Dow Jones US Banks Index	DJBI
	S&P 500 Bank Index	S&P 500
COVID-19	US infection cases	US COV-19
	Global infection cases	GLOBAL COV-19
Oil Price	WTI crude oil price	CRUDE OIL
US EPU	US EPU index	US EPU
Stock volatility	VIX US stock volatility	VIX
Economic activity	Baltic Dry Index	BDI

2.2 Wavelet analysis

For examining the lead-lag association among COVID-19, oil price, EPU, Baltic dry index, and bank indices, the CWT (wavelet coherence) is considered to find out the local correlation between two time series in time–frequency space. Although CWT (wavelet coherence) is widely applied in geophysics and many other engineering areas (Masset 2001; Alexandridis and Zapranis 2013), this method has become reliable in finance and economics in the recent days (Kim and In 2005; Vacha and Barunik 2012; Saiti 2012; Ko and Lee 2015; Bouri et al. 2017). Let W_x and W_y be the CWT of the signals $x(\cdot)$ and $y(\cdot)$, the cross wavelet power will be $|W_{xy}| = |W_x W_y|$ which illustrates the spatial covariance of the two time series for each frequency and scale (Hudgins et al. 1993). The coherence of the wavelet is established as the wavelet cross spectrum modulus generalized to the single spectrum and it is also helpful in illustrating the intervals of frequency and time when two trends have high reactivity.

Generally, a continuous wavelet transform (CWT) is capable of dividing a continuous-time matrix to wavelets. The continuous wavelet transform has the capacity to create a time–frequency image of a signal that provides strong localization of frequency and time. Since this technique has a minimum boundary for the unsure product, it contains both frequency and time by localizing the continuous wavelet transforms. Gencay et al. (2002) mentioned about the major benefit of CWT is that it can be defined in time (Δt) and in frequency ($\Delta \omega$) or in both by localizing CWT. Shahbaz et al. (2014) also noted that as there is a minimal limit for the unsure product, both Δt and $\Delta \omega$ must be properly interpreted. In this study, we have considered the Morlet wavelet, a popular type of wavelet most often used in recent times. The reason behind choosing Morlet wavelet is that this technique has the capacity of providing phase information which is a local measure of the phase delay or features of correlation between the fluctuations of the two series as a function of both frequency and time. The phase information is defined by the direction of the arrow. The Morlet wavelet equation, as such Torrence and Compo (1998) defined in the following:

$$\psi_0(\eta) = \pi^{-1/4} e^{i\omega_0\eta} e^{-\left(\frac{1}{2}\right)\eta} e^{-\frac{1}{2}\eta^2} \quad (1)$$

where dimensionless frequency $=\omega_0$ and time $=\eta$. As the Morlet wavelet (with $\omega_0=6$) technique provides balance between frequency localization and time, it is a perfect option for feature extraction. The motivation behind applying this method is that it serves as a band pass filter to the time series. The wavelet is stretched in time by varying its scale (s), so that $\eta=s \cdot t$ and normalizing it to have unit energy. $\delta t(x_n, n=1, \dots, N)$ is defined as the couple of x_n with the scaled and normalized wavelet (Shahbaz et al. 2014). The equation is:

$$W_n^x(s) = \sqrt{\delta t/s} \sum_{n'=1}^n x_{n'} \psi_0 \left[n' - n \left(\frac{\delta t}{s} \right) \right] \quad (2)$$

Monte Carlo method has been applied for estimating the statistical significance level of the wavelet coherence. Thick black contour represents the 5% significance level against the null hypothesis of red noise where black thin line illustrates the cone of influence. Arrows pointed right-down or left-up, mean the first variable is leading to the second variable. Arrows pointed right-up or left-down, mean the second variable is leading to the first variable.

3 Results and discussions

3.1 Summary statistics and time series trend

Table 2 illustrates the summary statistics of S&P 500 banks index, Dow Jones US banks index, US Covid-19 daily cases, Global Covid-19 daily cases, Baltic dry index, Crude oil price, US economic policy uncertainty, and stock volatility. We

Table 2 Summary statistics

	S&P 500	DJI	US COV-19	GLOBAL COV- 19	BDI	CRUDE OIL	US EPU	VIX
Mean	260.48	356.95	30916.99	157651.50	1050.21	36.97	310.45	31.43
Median	247.36	340.14	30521.00	126516.00	839.00	39.85	287.17	28.00
Maximum	368.59	505.22	88,130.00	511285.00	2097.00	58.38	866.86	82.69
Minimum	192.40	263.42	0.00	97.00	393.00	-37.63	22.25	12.85
Std. Dev	43.22	59.30	21634.19	126658.30	518.13	11.34	158.75	12.78
Skewness	1.52	1.53	0.16	0.51	0.25	-1.78	0.69	1.62
Kurtosis	4.21	4.23	2.28	2.42	1.50	11.26	3.34	6.13
Jarque-Bera	88.51	89.96	5.13	11.39	20.72	671.88	16.76	167.63
Probability	0.00	0.00	0.08	0.00	0.00	0.00	0.00	0.00
Observations	199	199	199	199	199	199	199	199

Source: Authors' estimation

noticed that the average of daily US COVID-19 cases is 30916.99, ranging from a minimum number of 0 to a maximum number 88130. The average value of both US COVID-19 and global COVID-19 cases depicts the highest level of fluctuation compared to the other because of their high standard deviation. The mean value of S&P bank index and DJ bank index are 260.48 and 356.95 respectively. The Jarque-Bera test hints the non-normal essence in all the variables.

The following Fig. 1 presents the time series trend of the variables used in this study.

3.2 Wavelet results

In order to explore the relationship between the variables, wavelet coherency has been applied in this study. The Wavelet Coherence plots (WTC) plots are depicted in Fig. 2, 3, 4, 5, 6, and 7. In this study, six groups of WTCs have been applied ((i) US COVID-19 new affected cases (ii) Global COVID-19 new affected cases (iii) VIX stock volatility (iv) US economic policy uncertainty (v) Baltic dry index, and (vi) Crude oil prices) on two US bank indices up to the scale of 64 days. Here, the vertical axis represents the investors' holding period of investment horizon (e.g. 2–4 days, 4–8 days, and so on.), while, the horizontal axis represents number of trading days during 21st January 2020 to 30th October 2020. In our wavelet analysis, we used natural logarithm form of every variables as the data are of different nature e.g. index data, price etc.

Figure 2 illustrates the wavelet coherency between the US bank index (both Dow Jones US banks index and S&P 500 banks index) and the US COVID-19 affected cases. In Fig. 2(a), The WTC plot for US COVID-19 daily reported cases and Dow Jones US banks index reveals strong dependence at the beginning, the mid, and the end of the study period. However, the dependences are of 4 to 8 days' frequency bands in the beginning and of 32 to 64 days' frequency bands in the middle. The US banks seems to react to the 'bad news' regarding COVID-19, such as the first reported COVID-19 cases in the US on January 19. This scenario may also be influenced by the sharp decline of oil price, stock market crash, and COVID-19 fears. Furthermore, the arrows are mostly turned left and up, indicating that the COVID-19 is leading the Dow Jones US banks index in this anti-cyclic scenario. Occasionally, the arrows face towards right and down, indicating a consistent led-lag association between the variables. However, we observe some right-oriented arrows during the period of mid-May to early-July depicting positive association between the variables. Such situation may be influenced by the sudden steep growth in stock volatility (as shown in the time series trend), which increased a temporary increase in banks' trading revenue. Nonetheless, such scenario reveals the short-run inconsistency in the financial market. Overall, similar results are reported in Fig. 2(b) while analyzing the COVID-19 and S&P 500 banks index. Therefore, the results are robust across both the indices of US banks used in this study.

In Fig. 3, we present the wavelet coherency between global COVID-19 cases and US banks indices. The results are similar to what is reported in the Fig. 2 in terms of US COVID-19 cases. However, the overall dependency between global

Fig. 1 Time series trends of DJBI, S&P 500, US COV-19, Global COV-19, VIX, US EPU, BDI and Crude Oil. Data Source: Thompson Reuters database

Fig. 2 **a** WTC: US COVID vs Dow Jones. **b** WTC: US COVID vs S&P 500

Fig. 3 **a** WTC: Global COVID vs Dow Jones. **b** WTC: Global COVID vs S&P 500

Fig. 4 **a** WTC: VIX vs Dow Jones. **b** WTC: VIX vs S&P 500

Fig. 5 **a** WTC: US EPU vs Dow Jones. **b** WTC: US EPU vs S&P 500

Fig. 6 **a** WTC: BDI vs Dow Jones. **b** WTC: BDI vs S&P 500

Fig. 7 **a** WTC: Crude Oil vs Dow Jones. **b** WTC: Crude Oil vs S&P 500

COVID-19 cases and US banks is comparatively weaker than that of US COVID-19 cases and US banks. This finding indicates that the influence of US COVID-19 situation is greater than the influence of global COVID-19 cases.

The association between stock volatility (VIX) and US banks indices is reported in Fig. 4. Figure 4(a) presents the WTC plot for VIX and Dow Jones US banks index. Here, the result reveals strong dependence between the variables throughout the study period. The strongest dependency is observed in the middle of the sample period. Furthermore, most of the arrows point towards left, indicating a negative association between the variables. The arrows pointed towards left and upward indicate that VIX negatively leads the Dow Jones US banks index. The evidence presented in Fig. 4(b) report similar results while studying the stock volatility and S&P 500 banks index. Our findings are in line with Rashid and Ilyas (2018) where they found that stock market volatility has strong negative influences on return, assets and equity of the banks.

The wavelet coherency between US EPU and US banks indices is presented in Fig. 5. Figure 5(a) reports findings regarding the Dow Jones US banks index and Fig. 5(b) reports findings for the S&P 500 banks index. Here, Fig. 5(a) depicts small islands of strong dependence throughout the study period. The dependences are mostly of 4 to 8 days' frequency bands. However, the impacts are of 32 to 64 days' frequency bands in the middle of the study period. Furthermore, the majority of arrows point towards left and up, depicting a negative led-lag association between the variables where US EPU leads the Dow Jones US banks index. The results are robust in terms of S&P 500 banks index reported in Fig. 5(b).

In Fig. 6, we present the wavelet coherence plots between BDI and US banks indices. Figure 6(a) reveals that the relationship between the variables is not consistent throughout the study period. Arrows pointing towards almost every direction depict inconsistency in the lead-lag association between the variables. Moreover, the small islands of black contours scattered throughout the study period reveals an overall weak association between the Baltic Dry Index and Dow Jones US banks index. Similar results are reported in Fig. 6(b) for S&P 500 banks index.

The WTC plots of WTI crude oil price and US banks indices are presented in Fig. 7. Figure 7(a) hints that there is a positive association between oil price and Dow Jones banks index at the beginning of the study period. In the middle period (from May), most of the arrows are pointed right-up, suggesting that the return of Dow Jones bank index is positively driven by crude oil price. Although the overall relationship between the variables is not strong over the long-term period, small island of black contours scattered throughout the period reveal strong short-run dependence. Hesse and Poghosyan (2016) and Al-Khazali et al. (2017) have also found strong co-movements between bank performance and oil price. We report similar results in Fig. 7(b) for WTI crude oil and S&P 500 bank index.

4 Conclusion

This study analyzes the condition of banking sector in the US during the COVID-19 pandemic. More specifically, the influence of COVID-19, crude oil price, US economic policy uncertainty, Baltic dry index, and the stock market volatility on the US bank indices are addressed in this study. By using the daily data over the period of 21st January 2020 to 30th October 2020, the continuous wavelet approach (wavelet

coherence) has been adopted to explore which factor leads the banks indices in the US. Based on the results from the wavelet approach, it is evident that US COVID-19 cases have strongly driven the return of bank indices at the beginning, the mid, and the end of the study period. US banks response quickly with the increase of COVID cases, also people may feel uncertainty about the banks stability which ultimately reduced the return of bank indices. The rise of global COVID-19 cases also affects the US banks; however, its impact is not as strong as US COVID-19 cases. Moreover, both stock market volatility and US economic policy uncertainty have a strong and negative influence on the US banks indices in this pandemic time. We have also found that oil price drives the return of banks indices at both low and high frequencies throughout the study period. However, inconsistent results were reported for BDI and US banks indices throughout the study period. Such inconsistency may be influenced by the external factors driving global economic activity.

The results of this study offer new insights, practical implications, and prominent policy. It is apparent that economic policy uncertainty, stock market volatility, and COVID cases have strong impacts on the US banks indices in this pandemic time. Thus, the US banks requires strong regulatory actions and alternative survival techniques to maintain the stability of the banks. US policymakers may impose favorable policies for US banks to survive the pandemic.

Nonetheless, the results of this study should be taken with caution as only US banks indices are considered. Moreover, other exogenous variables may influence the performance of banks in the US. However, our study opens the way for many future research studies regarding the performance and stability of the banks in the time of COVID-19. Further studies can explore the stability of the banks by considering other nations. Additionally, the impact of COVID-19 on non-performing loans could be other area of study as it may hinder the stability of the banks.

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

Data availability Data will be made available upon request.

Compliance with ethical standards

Conflict of interest On behalf of all authors, the corresponding author states that there is no conflict of interest.

References

- Alexandridis, A. K., & Zapanis, A. D. (2013). Wavelet neural networks: A practical guide. *Neural Networks*, 42, 1–27.
- Al-Khazali, O. M., & Mirzaei, A. (2017). The impact of oil price movements on bank non-performing loans: Global evidence from oil-exporting countries. *Emerging Markets Review*, 31, 193–208.
- Ashraf, B. N., & Shen, Y. (2019). Economic policy uncertainty and banks' loan pricing. *Journal of Financial Stability*, 44, 100695.
- Baker, S. R., Bloom, N., & Davis, S. J. (2016). Measuring economic policy uncertainty. *The quarterly journal of economics*, 131(4), 1593–1636.

- Bordo, M. D., Duca, J. V., & Koch, C. (2016). Economic policy uncertainty and the credit channel: Aggregate and bank level US evidence over several decades. *Journal of Financial Stability*, 26, 90–106.
- Bouri, E., Gupta, R., Tiwari, A. K., & Roubaud, D. (2017). Does Bitcoin hedge global uncertainty? Evidence from wavelet-based quantile-in-quantile regressions. *Finance Research Letters*, 23, 87–95.
- Demir, E., Bilgin, M.H., Karabulut, G. and Doker, A.C. (2020). The Relationship between Cryptocurrencies and COVID-19 Pandemic. Available at SSRN 3585147.
- Fitch Ratings, 2020. US Banks Trading Revenue Surges on Coronavirus Volatility; Future Results Uncertain.
- Francis, B. B., Hasan, I., & Zhu, Y. (2014). Political uncertainty and bank loan contracting. *Journal of Empirical Finance*, 29, 281–286.
- Gencay, R., Selcuk, F., & Whitcher, B. (2002). Book review: An introduction to wavelets and other filtering methods in finance and economics. *WRM*, 12(3), 399.
- Goodell, J. W. (2020). COVID-19 and finance: Agendas for future research. *Finance Research Letters*, 35, 101512.
- Hesse, H. and Poghosyan, T. (2016). Oil prices and bank profitability: Evidence from major oil-exporting countries in the Middle East and North Africa. In *Financial Deepening and Post-Crisis Development in Emerging Markets* (pp. 247–270). Palgrave Macmillan, New York.
- Holshue, M. L., DeBolt, C., Lindquist, S., Lofy, K. H., Wiesman, J., Bruce, H., et al. (2020). First case of 2019 novel coronavirus in the United States. *New England Journal of Medicine*, 382, 929–936.
- Hu, S., & Gong, D. (2019). Economic policy uncertainty, prudential regulation and bank lending. *Finance Research Letters*, 29, 373–378.
- Hudgins, L.H., Mayer, M.E. and Friehe, C.A. (1993). Fourier and wavelet analysis of atmospheric turbulence. *Progress in wavelet analysis and applications*, pp. 491–498.
- Irresberger, F., Mühlhnickel, J., & Weiß, G. N. (2015). Explaining bank stock performance with crisis sentiment. *Journal of Banking & Finance*, 59, 311–329.
- Jeris, S. S., & Nath, R. D. (2020). Covid-19, oil price and UK economic policy uncertainty: Evidence from the ARDL approach. *Quantitative Finance and Economics*, 4(3), 503.
- Jin, J. Y., Kanagaretnam, K., Liu, Y., & Lobo, G. J. (2019). Economic policy uncertainty and bank earnings opacity. *Journal of Accounting and Public Policy*, 38(3), 199–218.
- Karabulut, G., Bilgin, M. H., & Doker, A. C. (2020). The relationship between commodity prices and world trade uncertainty. *Economic Analysis and Policy*, 66, 276–281.
- Karadima, M. and Louri, H. (2020). Economic policy uncertainty and non-performing loans: The moderating role of bank concentration. *Finance Research Letters*, p.101458.
- Khandelwal, P., Miyajima, M.K. and Santos, M.A.O. (2016). The impact of oil prices on the banking system in the GCC. *International Monetary Fund*.
- Kim, S., & In, F. (2005). The relationship between stock returns and inflation: new evidence from wavelet analysis. *Journal of Empirical Finance*, 12(3), 435–444.
- Ko, J. H., & Lee, C. M. (2015). International economic policy uncertainty and stock prices: Wavelet approach. *Economics Letters*, 134, 118–122.
- Li, Y., 27 February 2020. It took stocks only six days to fall into correction, the fastest drop in history. *CNBC*.
- Massel, S. R. (2001). Wavelet analysis for processing of ocean surface wave records. *Ocean Engineering*, 28(8), 957–987.
- Rashid, D. & Ilyas, M. (2018). Returns volatility in stock market and performance of banks: Evidence from Pakistan.
- Rashid, M., Hassan, M. K., & Yein, N. Y. (2014). Macroeconomics, investor sentiment, and Islamic stock price index in Malaysia. *Journal of Economic Cooperation and Development*, 35(4), 219–234.
- Saiti, B., 2012. Testing the contagion between conventional and Shari'Ah-compliant stock indices: Evidence from wavelet analysis. Available at SSRN 2088136.
- Shahbaz, M., Tiwari, A. K., & Tahir, M. I. (2014). Analyzing time–frequency relationship between oil price and exchange rate in Pakistan through wavelets. *Journal of Applied Statistics* 42(4), 690–704.
- Sharif, A., Aloui, C. and Yarovaya, L. (2020). COVID-19 pandemic, oil prices, stock market, geopolitical risk and policy uncertainty nexus in the US economy: Fresh evidence from the wavelet-based approach. *International Review of Financial Analysis*, p. 101496.
- Tan, Y. and Floros, C. (2012). Stock market volatility and bank performance in China. *Studies in Economics and Finance*.

- Torrence, C., & Compo, G. P. (1998). A practical guide to wavelet analysis. *Bulletin of the American Meteorological society*, 79(1), 61–78.
- Vacha, L., & Barunik, J. (2012). Co-movement of energy commodities revisited: Evidence from wavelet coherence analysis. *Energy Economics*, 34(1), 241–247.
- Worldometer. (2020). Coronavirus Pandemic. <https://www.worldometers.info/coronavirus/>
- Zhang, D., Hu, M., & Ji, Q. (2020). Financial markets under the global pandemic of COVID-19. *Finance Research Letters*, 36, 101528.

Publisher's Note Springer Nature remains neutral with regard to jurisdictional claims in published maps and institutional affiliations.