THE IMPACT OF COVID-19 ON ISLAMIC AND CONVENTIONAL STOCKS IN INDONESIA: A WAVELET-BASED STUDY

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ABSTRACT

The recent literature shows that COVID-19 has impacted stock markets around the world in many ways. In this paper, we examine the reaction of the Indonesian stock market to COVID-19. We apply the continuous wavelet coherence methodology to daily COVID-19 related deaths and daily conventional and Islamic stock indices in Indonesia. We find that COVID-19 negatively impacts the returns of both indices and enhances their volatility. We find the Islamic stock index to be more volatile as compared to its conventional counterpart during the COVID-19 outbreak.

I. INTRODUCTION

The COVID-19 pandemic started in latter part of 2019 in China (Ali, Alam, and Rizvi 2020). Currently, COVID-19 has infected over fourteen million people and nearly 600,000 people have died globally[1]. The effects of COVID-19, in terms of its scale, seems to be far from determined. In the earlier stages, it was declared as an epidemic disease by World Health Organization, but on 11ᵗʰ March, 2020 the organization declared it a pandemic[2]. The stock markets worldwide have seen huge losses during the pandemic period (see Al-Awadhi, Al-Saifi, Al-Awadhi, and Alhamadi 2020).

Indonesia is forth most populated country in the world[3]. If we compare Indonesia with other South-East Asian countries, the country does not seem to be doing very well with respect to handling the pandemic, owing to its large population size and lower per capita income (Djalante et al., 2020). Since it is one of the most important countries in the South-East Asian region (Rattanasevee, 2014), it would be interesting to see how the COVID-19 pandemic impacted Indonesia's stock market. In addition to this, Indonesia is one of the very few countries that reformed its financial market to position it as a global Islamic finance hub (Diela, 2017; Juhro, Narayan, Iyke, and Trisnanto, 2020). The Indonesian stock market hosts both Islamic and conventional stocks. As per Juhro et al. (2020), the Islamic stock market is vital for Indonesia's growth. Islamic stocks are, at least, theoretically considered to be more linked with real activity and are expected to experience a lower impact of the health crisis. This is why we explore whether the impact of COVID-19 related deaths on conventional stocks is different from Islamic stocks. The nature of the Islamic stock market makes Indonesia a very interesting focus of our study.

Theoretically, we are guided by the investor over- and underreaction behavioral theories of Daniel, Hirshleifer, and Subrahmanyam (1998), Hong and Stein (1999), and Hong, Torous, and Valkanov (2007). The stakeholders in the stock market, when it comes to COVID-19, are investors. When an extraordinary crisis like COVID-19 happens, about which information is scarce, the initial reaction of investors is expected to be one of overreaction due to the uncertainty caused by the crisis (Iyke, 2020a). But as time passes, information becomes available to investors, who in turn become more certain about future events and make their investment decisions with more comfort (Phan & Narayan, 2020).

The empirical literature on the impact of COVID-19 on stock markets is growing rapidly. Recent works show that the Chinese COVID-19 related deaths and cases have mixed impacts on stock markets (Albulescu, 2020). Al-Awadhi et al. (2020) and Ali et al. (2020) are two of the earliest studies which directly study the impact of COVID-19 on global financial markets. Besides, Devpura (2020), Ertuğrul, Güngör, and Soytaş (2020), Huang and Zheng (2020), Haroon and Rizvi (2020), He, Sun, Zhang, and Li (2020), Iyke (2020a, b, c), Iyke and Ho (2021), Narayan (2020a, b, c), Phan and Narayan (2020), Prabheesh, Padhan, and

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[1] See https://www.worldometers.info/coronavirus/
[2] See https://www.who.int/director-general/speeches/detail/who-director-general-s-opening-remarks-at-the-media-briefing-on-covid-19---11-march-2020
[3] See https://www.worldometers.info/world-population/population-by-country/

Garg (2020), Sharma (2020), and Vidya and Prabheesh (2020) are some of the most relevant studies on the topic. The studies on individual countries are primarily limited to the US, European countries, and China. In this paper, we focus on a very important emerging market, i.e. Indonesia, and examine the COVID-19 pandemic on its Islamic and conventional equities.

We first followed a descriptive approach by showing the stock market numbers during different phases of the COVID-19 pandemic. We follow Ali et al. (2020) and divide our sample based on two phases of COVID-19, namely (1) the epidemic phase and (2) the pandemic phase. The epidemic phase/period starts from January 1, 2020 and lasts until March 10, 2020 and the pandemic phase/period starts from March 10, 2020 to date.[4] In addition, we consider: the global spread, Phase I, whereby almost all COVID-19 spread was limited to China; Phase II, spread of COVID-19 to Europe; Phase III, spread of COVID-19 in North America until the announcement of stimulus packages; and Phase IV from the time announcement of stimulus packages till date. Secondly, we employ the continuous wavelet coherence methodology suggested by Grinsted, Moore, and Jevrejeva (2004) to examine the impact of daily COVID-19 related deaths on daily prices of conventional and Islamic stock indices in Indonesia. Our findings indicate that that COVID-19 predominantly negatively impacts the returns of both indices and enhances their volatility. We find the Islamic stock index to be more volatile during COVID-19, as compared to its conventional counterpart. Our findings are robust across different proxies of COVID-19.

This paper adds to the rapidly growing literature on the financial impacts of COVID-19, by exploring the impact of the disease outbreak on the Indonesian stock market. Additionally, as there is limited literature addressing the impact of COVID-19 on the stock markets of emerging economies, this study contributes to the literature on this crisis and stock markets of emerging economies. Thirdly, we also add to the literature related to Islamic versus conventional equites, by considering how both equities respond to COVID-19.

In the next section, we discuss our data and methodology. In Section III, we show the results and analyze them. In Section IV, we provide the conclusion.

II. DATA AND METHODOLOGY
A. Data
We compile a dataset on daily COVID-19 related deaths in Indonesia and returns of the Jakarta Islamic Index (JAKISL) and its conventional counterpart, the Jakarta Composite Index (JCI). We collect the COVID data from ourworldindata.org and the JAKISL and JCI returns data from investing.com. Our sample period starts from 1 January 2020 till 30 November 2020, a total of 222 observations.

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[4] See https://www.who.int/dg/speeches/detail/who-director-general-s-opening-remarks-at-the-media-briefing-on-covid-19---11-march-2020

B. Methodology

To calculate the volatility of the indices, we employ the exponential generalized autoregressive conditional heteroskedasticity (EGARCH) model. The reason for using the EGARCH model is that financial markets react to bad and good news differently and the EGARCH model captures these dynamics (Iyke & Ho, 2020). This model has been employed extensively in the literature (Rizvi, Arshad, & Alam, 2018; Iyke & Ho, 2021; Yu & Hassan, 2008). The EGARCH model is considered superior to other models because it allows for relatively more stable optimization of routines, and it does not have any parameter constraints. The variance equation of the EGARCH model is as follows:

$$ln\sigma_{j,t}^2 = \omega_t + \beta_j \ln(\sigma_{j,t-1}^2) + \gamma \frac{\varepsilon_{t-1}}{\sqrt{\sigma_{t-1}^2}} + \alpha \left[\frac{|\varepsilon_{t-1}|}{\sqrt{\sigma_{t-1}^2}} - \sqrt{\frac{2}{\pi}} \right] \tag{1}$$

where $\sigma_{j,t}^2$ indicates the conditional variance and ω_t indicates a conditional density function. The parameter α shows the GARCH effect or the systematic effect; β denotes the persistence in conditional volatility; and γ is the leveraging effect.

We employ the continuous wavelet coherence methodology to establish the relationship between COVID-19 deaths and returns and volatilities of JCI and JAKISL indices. The continuous wavelet coherence approach is quite different from standard time series methodologies. Unlike them, wavelet coherence permits observing the co-movement between two time series, both in terms of time and frequency. This approach employs a bivariate model constructed on a continuous wavelet transform. This permits for a number of easily scaled localizations (Rua & Nunes, 2009). We employ the wavelet coherence methodology by means of transformation and coherence as in Goodell and Goutte (2020).

As shown by Torrence and Compo (1998), the cross wavelet transform (CWT) of time-series variables, let's say x and y, is presented using their own specific CWT as shown below:

$$W_n^{xy}(u, s) = W_n^x(u, s) * W_n^y(u, s) \tag{2}$$

where $W_n^x(u,s)$ is a transform form of x and $W_n^y(u,s)$ is a transform form of y. u represents location, s represents scale, and * represents complex conjugate. CWT takes care of the covariance between x and y at each scale.

Following Torrence and Webster (1999), the wavelet coherence based co-movement between x and y is given by:

$$R^2(u, s) = \frac{|S(s^{-1}W^{xy}(u,s))|^2}{S(s^{-1}|W^x(u,s)|^2)S(s^{-1}|W^y(u,s)|^2)} \tag{3}$$

In Equation (3), $R^2(u,s)$ denotes the wavelet squared coherence, which normally lies between 0 and 1, and S is a smoothing operator. The wavelet coherence phase difference is given by:

$$\partial_{xy}(u,s) = tan^{-1}\left(\frac{Ik\{S(s^{-1}W^{xy}(u,s))\}}{R\{S(s^{-1}W^{xy}(u,s))\}}\right) \tag{4}$$

In Equation (4), *Ik* represents the imaginary parts and *R* denotes the real parts of the smoothed CWT.

III. ANALYSIS

Figure 1 shows the COVID-19 related deaths in Indonesia to date. The first death was recorded in the second week of March 2020 and since then, Indonesia has seen a growing trend in COVID-19 related deaths. Figure 2 shows the returns of Islamic and conventional stock indices over the study period. It appears that both conventional and Islamic stock indices have the similar pattern throughout the study period.

Figure 1.
COVID-19 Deaths in Indonesia

This figure shows the number of COVID-19 related deaths in Indonesia from January 2020 to November 2020. The number of cases are given on the Y-axis whereas dates are given on the X-axis.
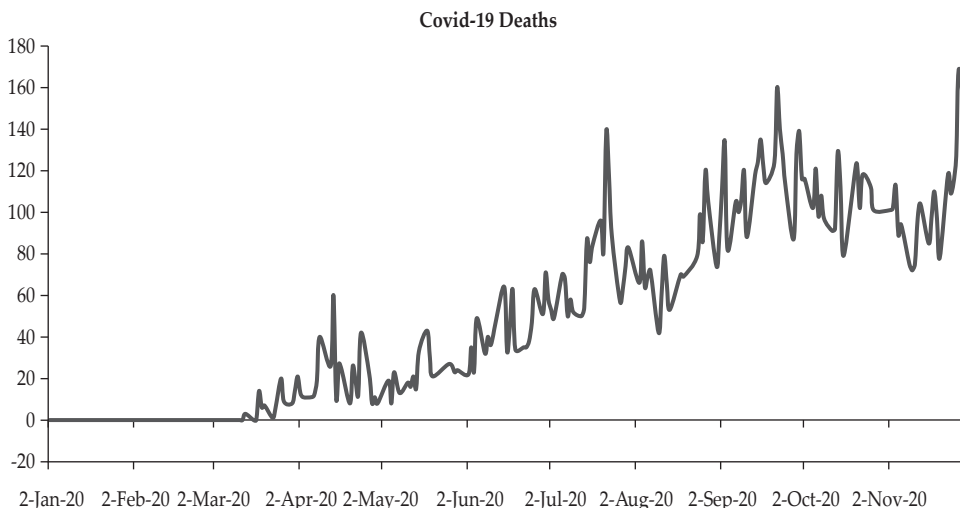

Covid-19 Deaths

Figure 2.
JCI and JAKISL Returns

This figure shows the returns of JCI and JAKISL indices from January 2020 to November 2020. The returns for both indices are given on the Y-axis whereas dates are given on the X-axis.
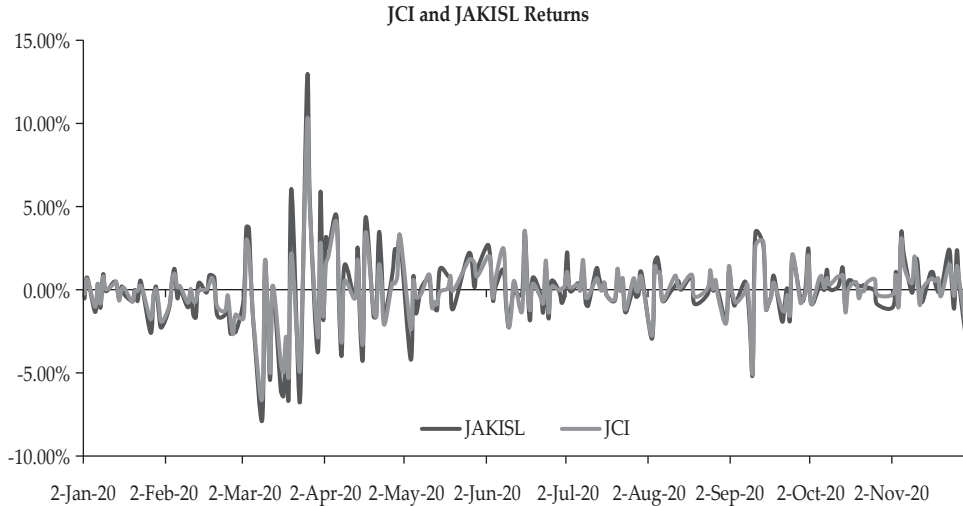

Table 1 shows the descriptive statistics on COVID-19 related deaths and the returns and volatility of the stock indices. We observe that the Islamic stock index show higher volatility as compared to the conventional stock index, whereas the average returns of both indices remained the same. The returns of the Islamic stock index vary from -7.84% to 12.81%, while the returns of the conventional stock index vary from -6.58% to 10.19%.

Table 1.
Descriptive Statistics of Variables

This table presents the descriptive statistics on Deaths, JAKISL returns, JCI returns, JAKISL volatility and JCI volatility. The sample is from January 2020 to November 2020.

Description	Deaths	JAKISL Returns	JCI Returns	JAKISL Volatility	JCI Volatility
Mean	51.73	-0.046%	-0.039%	0.077%	0.083%
Standard Deviation	45.94	2.166%	1.730%	0.272%	0.568%
Minimum	0.00	-7.840%	-6.580%	0.022%	0.013%
Maximum	169.00	12.810%	10.190%	3.583%	8.312%
Skewness	0.39	0.50	0.33	10.79	13.88
Kurtosis	-1.17	6.74	6.67	129.76	200.00
Jarque-Bera	18.23	428.91	415.54	160046.10	377115.26

Also, Table 2 shows that both the Islamic and conventional stock indices recorded negative returns of -0.47% and -0.39%, respectively, during the Epidemic phase. This could be attributed to the uncertainty induced by COVID-19. During

the Pandemic phase, the stock market seems to have recovered from the COVID-19 induced uncertainty and recorded positive average returns. But it would be a simplistic to conclude based on the average return of around eight months of the pandemic period. In order to understand more about how returns changed throughout the period under study, we further divided our sample into four phases. The statistics related to the four phases are presented in Table 3. As far as volatility is concerned, the volatility of both JCI and JAKISL indices increased as we move from the Epidemic to the Pandemic phase. The negative part of returns and the higher volatility suggests that investor sentiment and the COVID-19 induced uncertainty have a significant influence on the Indonesian stock market.

Table 2.
Statistics for Returns and Volatility for Epidemic and Pandemic Periods

This table presents the descriptive statistics on JAKISL and JCI returns and volatility for Epidemic and Pandemic time period, whereby the World Health Organization reported that the Epidemic period started from January 1, 2020 till March 10, 2020 and Pandemic period started from March 10, 2020 till date.

Description	JAKISL Returns	JCI Returns	JAKISL Volatility	JCI Volatility
Panel A: Epidemic Period				
Mean	-0.47%	-0.39%	0.05%	0.03%
Standard Deviation	1.71%	1.39%	0.05%	0.01%
Minimum	-7.84%	-6.58%	0.03%	0.02%
Maximum	3.74%	2.94%	0.30%	0.09%
Skewness	-1.18	-1.51	4.29	2.40
Kurtosis	6.58	7.23	19.20	5.84
Jarque-Bera	99.68	125.55	902.87	116.67
Panel B: Pandemic Period				
Mean	0.074%	0.056%	0.066%	0.051%
Standard Deviation	2.264%	1.804%	0.153%	0.144%
Minimum	-6.630%	-5.200%	0.022%	0.013%
Maximum	12.810%	10.190%	1.619%	1.561%
Skewness	0.63	0.51	8.08	8.38
Kurtosis	6.39	6.26	73.26	78.78
Jarque-Bera	306.31	289.79	40571.47	46763.26

As we see in Table 3, the returns and volatilities of JCI and JAKISL vary across the four phases, starting from the beginning of the COVID-19 outbreak in China (i.e. when China was the epicenter, Phase I), the spread of COVID-19 in Europe (Europe became the epicenter, Phase II), then in phase III, and when COVID-19's epicenter moved to the US until the first stimulus packaged was announced by the US and followed by other countries including Indonesia. Table 3 provides a more comprehensive picture as compared to Table 2, because in Table 3, we split the time period into four phases. We can see that the average returns of both JAKISL and JCI kept on declining from phase I until phase III, i.e. from the COVID-19 outbreak until the stimulus packages were announced. This can be linked to media coverage, which created uncertainty leading to negative investor sentiments that resulted in the decline in returns and an increase in the volatility of stocks (Donadelli, 2015; Engelberg & Parsons, 2011; Iyke & Ho, 2021; Peress, 2014).

After the announcements of the stimulus packages, investors seem to have gotten some confidence leading to an increase in stock returns by the beginning of July 2020. Another significant point to consider is the claim by the Chinese government that the COVID-19 spread is under control by the end of March 2020[5], which would have positively impacted the Indonesian stock market because of the country's strong link with China. The returns of JAKISL remained lower as compared to JCI during the first two phases, but, as we moved to the third phase, JCI returns took a bigger hit and declined below JAKISL returns. In the fourth phase, returns of JAKISL remained slightly higher than JCI. As far as volatility is concerned, JCI seemed to be more stable as compared to JAKISL across the different phases of COVID-19. We do not observe a significant rise in volatility of both the indices across the different phases. This may be owed to the idiosyncratic factors of the Islamic indices, such as being shariah compliant and being immune to speculative risks (Ali et al., 2020; Juhro et al., 2020). A possible explanation is that, since Islamic indices can only have shariah compliant stocks, the universe of constituents for Islamic indices is much smaller as compared to their conventional counterparts. So, the conventional indices have a higher probability of being well diversified.

Table 3.
Statistics for Returns and Volatility for Global Spread Phases

This table presents the descriptive statistics on JAKISL and JCI returns and volatility for the four phases of COVID-19, whereby Phase I shows deaths and localized cases in China from Jan 1, 2020 to Feb 14, 2020, Phase II represents spread in Europe from Feb 15, 2020 to Feb 28, 2020, Phase III shows the spread started in US till the announcement of stimulus packages from March 1, 2020 to March 20, 2020, and Phase IV starts from stimulus package announcement till date.

Description	JAKISL Returns	JCI Returns	JAKISL Volatility	JCI Volatility
Panel A: PHASE I				
Mean	-0.37%	-0.21%	0.04%	0.03%
Standard Deviation	0.91%	0.69%	0.01%	0.01%
Minimum	-2.60%	-1.94%	0.03%	0.02%
Maximum	1.23%	0.95%	0.10%	0.04%
Skewness	-0.60	-0.65	2.11	1.70
Kurtosis	0.01	0.32	5.70	4.57
Jarque-Bera	1.93	2.40	67.14	43.37
Panel B: PHASE II				
Mean	-0.91%	-0.89%	0.05%	0.03%
Standard Deviation	1.40%	1.09%	0.01%	0.01%
Minimum	-2.62%	-2.69%	0.03%	0.02%
Maximum	0.87%	0.71%	0.07%	0.05%
Skewness	0.15	-0.41	2.65	2.38
Kurtosis	-1.72	-0.72	7.64	6.24
Jarque-Bera	1.27	0.49	36.02	25.65

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[5] See https://www.reuters.com/article/us-healthcare-coronavirus-china/new-coronavirus-infections-may-drop-to-zero-by-end-march-in-wuhan-chinese-government-expert-idUSKBN20S02J

Table 3.
Statistics for Returns and Volatility for Global Spread Phases (Contined)

Description	JAKISL Returns	JCI Returns	JAKISL Volatility	JCI Volatility
Panel C: PHASE III				
Mean	-1.70%	-1.90%	0.11%	0.05%
Standard Deviation	4.29%	3.24%	0.08%	0.02%
Minimum	-7.84%	-6.58%	0.03%	0.02%
Maximum	6.06%	2.94%	0.30%	0.09%
Skewness	0.25	0.04	3.37	3.79
Kurtosis	-1.02	-1.36	11.85	14.52
Jarque-Bera	0.81	1.16	116.21	167.69
Panel D: PHASE IV				
Mean	0.219%	0.188%	0.057%	0.044%
Standard Deviation	2.027%	1.646%	0.131%	0.127%
Minimum	-6.630%	-5.010%	0.022%	0.013%
Maximum	12.810%	10.190%	1.619%	1.561%
Skewness	1.29	1.16	10.60	10.63
Kurtosis	9.24	8.47	124.35	124.00
Jarque-Bera	632.75	529.74	109403.22	108822.38

In the second part of analysis, we discuss our wavelet coherence estimates. Figures 3 and 4 illustrate the coherence and phase difference between the COVID-19 related deaths and JAKISL and JCI returns, respectively. The time component is shown on the horizontal axis, whereas the frequency component is shown on the vertical axis. This spans from 1 scale representing just one day up to 16 representing 16 days or more. The black outlined shapes show areas with 5% significance level. This is projected by Monte Carlo simulation through phase-randomized surrogate series. The curved lines represent cone of influence. The yellow color in the figures indicate higher level of coherency, whereas the blue color indicates lower level of coherency to entitle the level of co-movement. In other words, strong co-movement is represented by the yellow color, whereas weak co-movement is indicated by the blue color.

Figure 3.
Wavelet Coherence Between Daily COVID-19 Deaths and JCI Returns

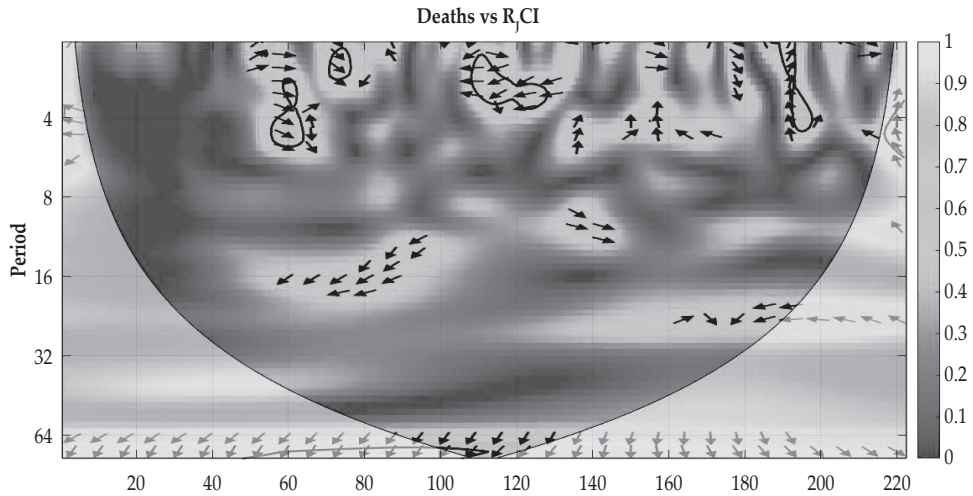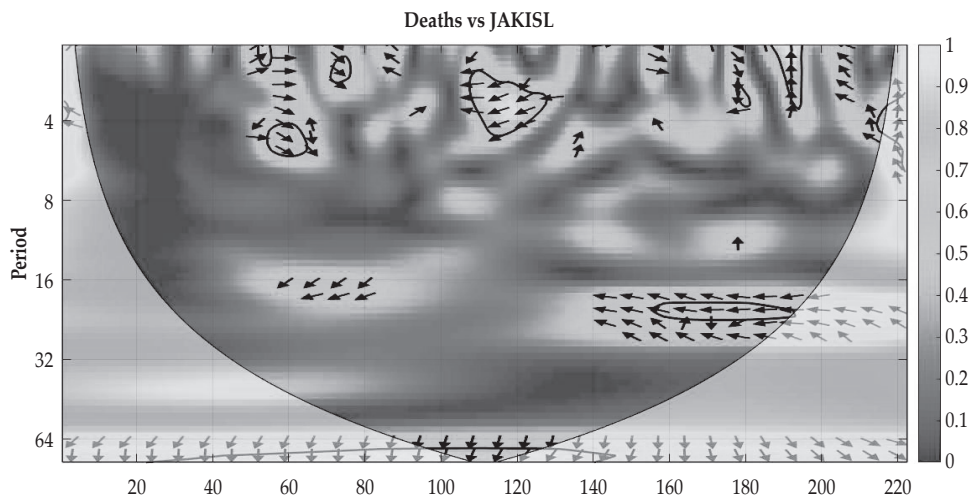This figure shows the wavelet coherence results between daily COVID-19 deaths and JCI returns.

Deaths vs R$_J$CI

Figure 4.
Wavelet Coherence Between Daily COVID-19 Deaths and JAKISL Returns

This figure shows the wavelet coherence results between daily COVID-19 deaths and JAKISL returns.

Deaths vs JAKISL

In Figure 3, we identify four significant co-movements between COVID-19 related deaths and JCI returns. The first one is in the last week of March 2020 across the 2-6 day frequency band. This is around the time when stimulus packages were announced in Indonesia. The second co-movement can be observed in the third week of April across 2-3 day band. The third co-movement spans from mid-June to mid-July across 2-4 day frequency band. The last co-movement is observed in the

second week of October, when the frequency day band remained around 0-5 day. We observe that, in the first and second coherence phase, the arrows are → and ↘, indicating an in-phase relationship and a positive correlation between deaths and JCI returns, respectively, whereas, in the third coherence in the months of June and July, we observe the arrows are ← and ↙, showing an in-phase relationship and a negative correlation between deaths and JCI returns, respectively.

In Figure 4, we identify five significant co-movements between deaths and JAKISL returns. The first one is in the third week of March 2020 across 4-6 day frequency band. This is around the time when stimulus packages were announced in Indonesia. The second co-movement can be observed in the end of April across 2-3 day band, the third spans from mid-June to mid-July across 2-5 day band, the forth spans from mid-August until mid-Oct for around 20-25 day band, and the fifth co-movement is observed in the second week of October for 0-3 day band. The most significant and strong coherence is the third one during the time period, when the COVID-19 became more accepted part of life and contained in most parts of the world. We observe the arrows are ← and ↙, indicating an in-phase relationship and a negative correlation between deaths and JAKISL returns, respectively. This coherence is similar to the one between deaths and JCI returns.

In Figure 5, we identify two significant co-movements between deaths and JCI volatility. The first one remained for the last three weeks of February across 0-2 day frequency band. This is during the epidemic phase, though no death was recorded in Indonesia at that point in time. The second co-movement can be observed in the month of October across a 3-4 day band. The second coherence is more important—we observe the arrows are ← and mostly ↖, generally indicating an out of phase relationship and a negative correlation between deaths and JCI volatility, respectively. In Figure 6, we identify four significant co-movements between deaths and JAKISL volatility. The first one remained for the last two weeks of April across 2-3 day frequency band. The second co-movement falls in the end of June across 2-3 day frequency band. The co-movement remained for only 3-4 days. The third co-movement can be observed in the last week of September across 0-2 day band, and the third coherence is observed in the month of October for 4-6 day band. The most significant and strong coherence is the last one. We observe the arrows are ← and mostly ↙, generally indicating in-phase relationship and a negative correlation between deaths and JAKISL volatility, respectively.

Figure 5.
Wavelet Coherence Between Daily COVID-19 Deaths and JCI Volatility

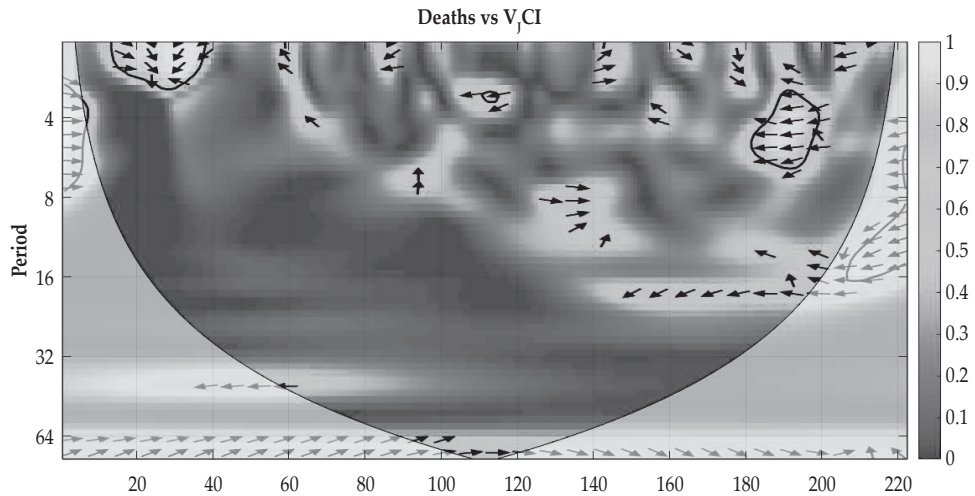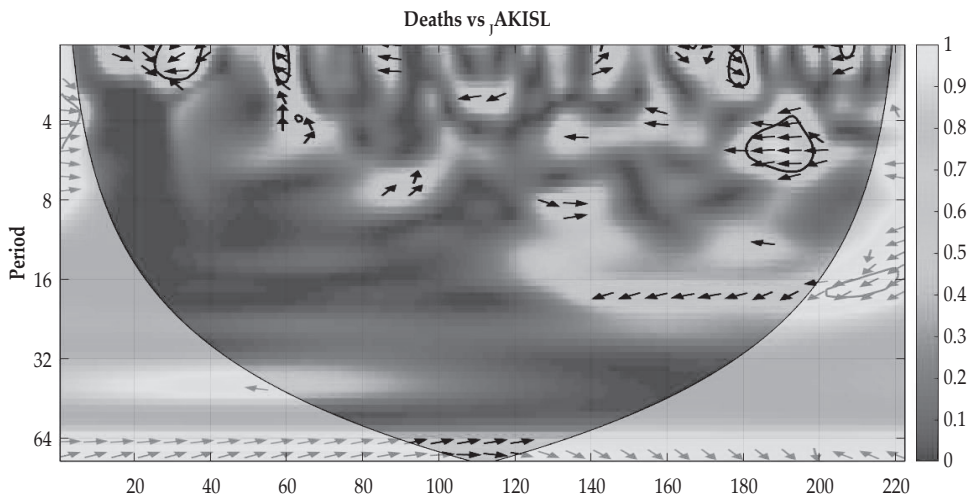This figure shows the wavelet coherence results between daily COVID-19 deaths and JCI volatility.

Deaths vs V$_J$CI

Figure 6.
Wavelet Coherence Between Daily COVID-19 Deaths and JAKISL Volatility

This figure shows the wavelet coherence results between daily COVID-19 deaths and JAKISL volatility.

Deaths vs $_J$AKISL

In order to add credence to our results, we use daily COVID-19 infections in Indonesia as an alternative proxy for the impact of COVID-19. The wavelet coherence results, using this proxy, are reported from Figures 7 to 10. Generally, we find very similar impact of infection on the returns and volatility of both indices. This shows that our results are robust across different proxies of COVID-19.

In summary, we mainly discover a negative co-movement of returns and COVID-19 deaths. In addition, we find a positive correlation between deaths and

the volatility of both the stock indices. Our findings, in terms of investor reactions, are in line with the findings of Hong and Stein (1999), Hong et al. (2007), and Iyke (2020a). We show that the intensity levels of the co-movements vary during the period under study, with a few brief periods even showing a positive correlation between COVID-19 deaths and returns. COVID-19 is an unprecedented event (Narayan, 2020c), which is expected to impact the way investors perceive uncertainty (Iyke & Ho, 2021).

Figure 7.
Wavelet Coherence Between Daily COVID-19 Infections and JCI Returns

This figure shows the wavelet coherence results between daily COVID-19 infections and JCI returns.
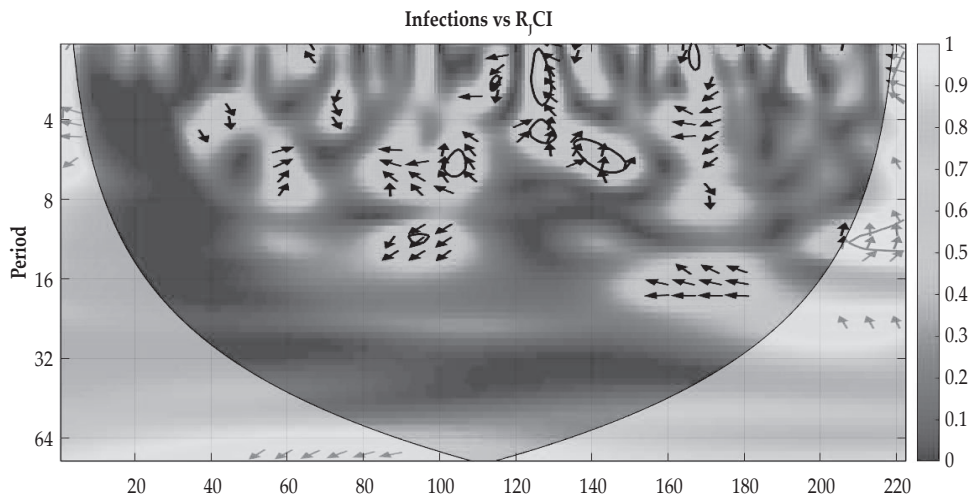

Figure 8.
Wavelet Coherence Between Daily COVID-19 Infections and JAKISL Returns

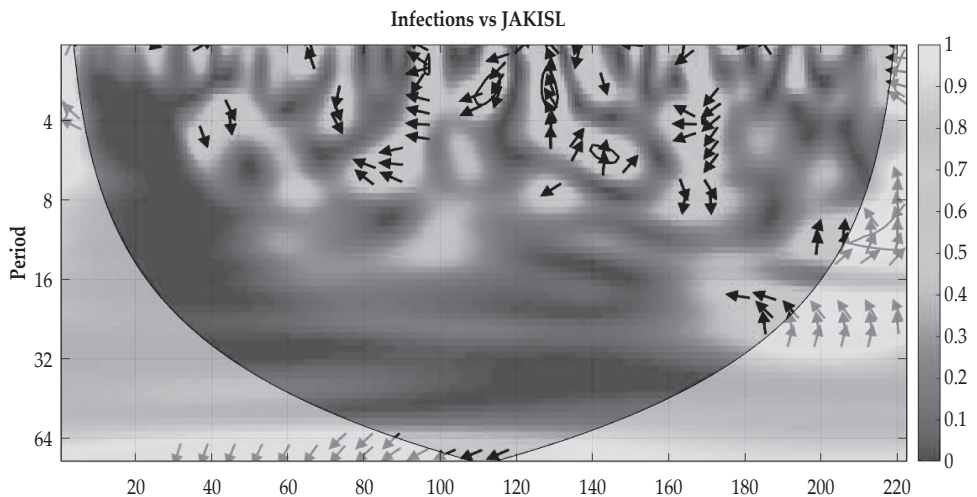This figure shows the wavelet coherence results between daily COVID-19 infections and JAKISL returns.

Figure 9.
Wavelet Coherence Between Daily COVID-19 Infections and JCI Volatility

This figure shows the wavelet coherence results between daily COVID-19 infections and JCI volatility.
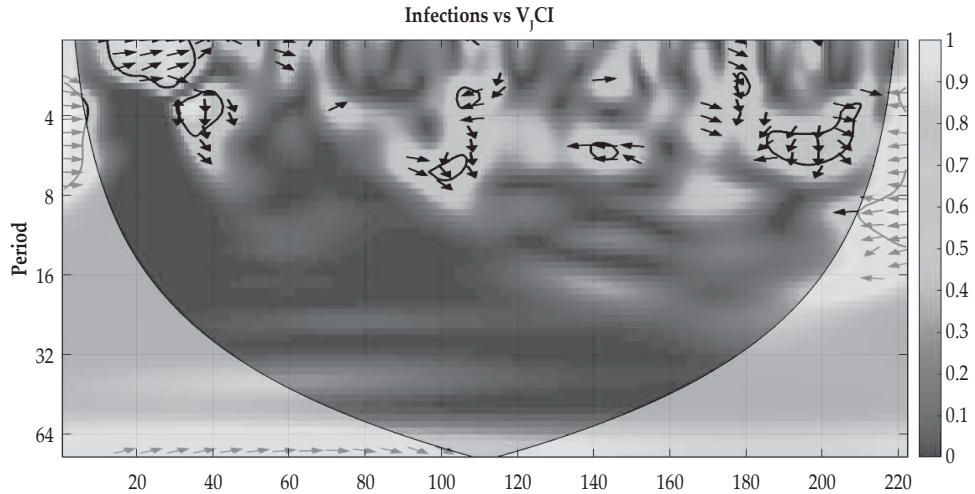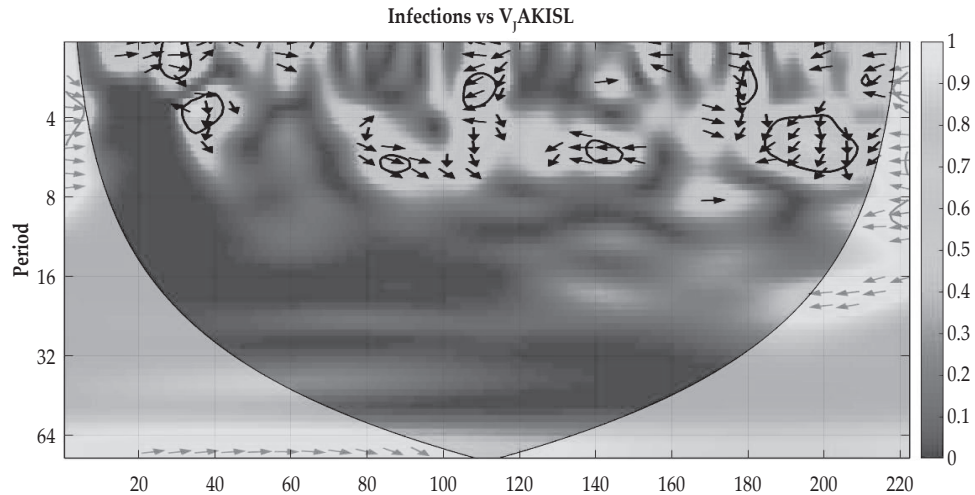

Infections vs V$_J$CI

Figure 10.
Wavelet Coherence Between Daily COVID-19 Infections and JAKISL Volatility

This figure shows the wavelet coherence results between daily COVID-19 infections and JAKISL volatility.

Infections vs V$_J$AKISL

IV. CONCLUSION

COVID-19 poses danger to global financial markets as it is associated with unforeseen levels of ambiguity. The Indonesian financial market also got affected by the crisis. We studied the impact of the COVID-19 crisis on the Indonesian stock market. Our findings suggest that COVID-19 has negatively impacted the returns of both Islamic and conventional stock indices. It has also enhanced the volatility of both the stock indices. We observed that the Islamic stock index is more volatile

as compared to its conventional counterpart during all phases of COVID-19. This study has implications for investors in the Indonesian stock market, by showing how both the Islamic and the conventional stock indices behaved during the crisis. Our results are robust across different proxies of COVID-19 crisis. This study adds to the rapidly growing literature on the financial impacts of COVID-19. Regulatory level policy making during unprecedented times like the pandemic could be an interesting topic for a future study.

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