Economy–energy markets nexus during COVID-19: A dynamic time–frequency analysis

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Abstract
We investigate dynamics between the economic activities and energy markets—both conventional and clean energy markets, with a sample of daily data from 1 January 2020 to 25 November 2020. We perform wavelet-based time–frequency techniques and measure the market volatility with continuous wavelet transforms. Besides, we use wavelet coherency to understand the co-movement of economic activities and energy markets and employ a nonlinear phase-difference technique to understand the time-varying causality between different series. Our continuous wavelet transform results show that all three market indices experience significant volatility in the coronavirus disease (COVID-19) period, notably during the initial period of the outbreak. The market volatilities are comparatively more substantial in the lower frequency band than the upper frequency, while the latter sustained longer in the markets. Moreover, wavelet coherency results show a strong correlation between the economic activity index and both energy market indices; however, the co-movement is significantly higher for the conventional energy market than the clean energy market. We further detect a positive and bi-directional causality between economic activities and energy market indices. Besides providing fresh and time-varying and frequency-varying relationship between global economic activities and the energy markets, which is currently lacking in the existing literature, our study has significant implications for the heterogeneous market participants in terms of improved price prediction accuracy. Furthermore, our findings can aid policymakers in decision making by showing that the dynamics between energy markets and economic activities change even within a short period, and imply that suitable constant policy interventions are necessary to avoid long-term predicament.

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Introduction

The rapid economic disruption triggered by the recent coronavirus disease 2019 (COVID-19) is destructive and has spillover effects as it generated demand and supply shocks virtually in almost all the areas of human endeavor. The pandemic-induced macro-economic crisis and the containment measures taken by governments in the forms of lockdown or travel ban to curb the spread of the virus have slowed down transport, trade, and economic activity across the globe. The Asian Development Bank estimated that global economic cost could be between $5.8 trillion and $8.8 trillion, equivalent to a loss of 6.4–9.7% in the global gross domestic product. Among all the sectors, such measures and the contraction in economic activities have set up a different dimension to the energy markets, precisely. Efforts to contain COVID-19 have frozen many global supply channels, while the fear of contagion is causing an unprecedented cutback in consumer demand. The COVID-19 pandemic-led lockdowns have steered to the biggest fall in energy demand in 70 years, and the energy sector comes out as one of the biggest losers during the pandemic.

The COVID-19 pandemic disrupted an array of energy markets, comprising the conventional oil, coal, gas, and renewable energy markets. The impact of the COVID-19 pandemic on the energy sector is further highlighted by the International Energy Agency (IEA). By quoting the IEA projection, Broom report a 6% fall in global energy use in 2020, which is more than seven times the impact of the global financial crisis of 2008. Thus, the outbreak of the COVID-19 pandemic has not only disrupted the global economy and supply chain; it has dramatic transformational effects on the energy markets. The pandemic-induced shock transpired globally, and the uncertainty indicators have pronounced effects on the historical volatility of energy markets. In the energy market, the investors’ sentiment was factually higher on the tail events, indicating that fearful investors rushed toward put options and paid an excess premium to protect from unprecedented risk prevailing in the energy market. Accordingly, the COVID-19 induced economic crisis has brought the biggest shock to the global energy markets in the last seven decades.

Traditionally, the relationship between energy markets and economic activities is dynamic and subject to rapid changes. Besides, existing literature streams recognize the impacts of pandemics on market performances. However, the energy market plunges due to the shocks generated by COVID-19 are unique. Notably, the COVID-19 pandemic differs from the comparable pandemics or epidemics due to its high contagiousness, which triggers a lot of uncertainty in the real economy and financial markets. Consequently, governments’ intent to manage the COVID-19 pandemic and mitigate the effects on economies exert a considerable downbeat impact on the global energy transition. Given the novel aspects of economic activities and energy markets during the COVID-19 pandemic, we investigate the economy-energy nexus through a dynamic time–frequency technique. We employ wavelet analysis to investigate the relationship in both time-varying and frequency-varying domains for economic activities and energy market indices. This technique has considerable benefit in analyzing the relationship among variables into several time scales without losing pertinent information, unlike conventional time-series analysis. Also, the technique helps deal with inherent time-series characteristics, such as structural break or non-stationarity, that may distort the findings.
We use Baltic Exchange Dry Index (BDIR) to identify the changes in economic activities, while we use S&P Global 1200 Energy Index (SPGER) and S&P Global Clean Energy Index (SPGCER) for the energy markets measurement. Precisely, we analyze the changes in the relevant market indices across different frequencies and periods using continuous wavelet transforms (CWTs) and measure their co-movements through wavelet coherence analysis. Also, we utilize a nonlinear wavelet phase-difference technique that allows us to derive the time-varying causality between different series. Our CWT results show that all three market indices experience significant volatility during COVID-19, notably during the initial period of the outbreak. The market volatilities are comparatively more substantial in the lower frequency band than the upper frequency, while the latter sustained longer in the markets. Moreover, wavelet coherence results show a strong correlation between the economic activity index and both energy market indices. However, the co-movement is significantly higher between BDIR and SPGER compared to BDIR and SPGCER relationship. Furthermore, our phase-difference analysis reveals a positive and bi-directional causality between BDIR and energy market indices.

While most recent studies analyze the impact of the pandemic using the COVID-19 cases or death on stock market indices, we analyze the volatility and contagion of economic activities and energy markets by using established market indices. Hence, we complement the current understanding with the inclusion of the energy sector, which is indicated as one of the hardest-hit sectors during the pandemic. Besides, most of the studies perform investigations focusing on a particular economy. In contrast, our research offers a global perspective of the crisis by considering indices representing global economic activities. Moreover, existing studies are remarkably concentrating on oil market dynamics. However, the renewable market has great significance in today’s world since it represents alternative energy and sustainable energy source that helps achieve sustainable development goals. Also, together with the conventional energy sources, renewable energy or clean energy usage are strongly connected to the level of economic activity and growth. Studies point out that COVID-19 has negatively affected market dynamics for renewables, impacting all stakeholders along the value chain. However, the impacts on clean energy markets have not been explored empirically yet.

With the empirical evidence, we contribute to the literature by providing a cross-discipline understanding of the linkages between health and economic crisis with fresh evidence from the COVID-19 pandemic. Our study further contributes to the financial crisis literature by empirically demonstrating how non-financial and non-economic factors can trigger financial and economic meltdowns. Furthermore, our study offers policymakers and governments an insight into the relationship dynamics of COVID-19. Notably, the interconnection between global financial markets keeps increasing in recent years and economies worldwide are linked more than anytime before, which may have impacted international investors’ decisions on asset allocation during this crisis. Hence, understanding the impact of COVID-19 on financial markets will be particularly important for investors and policymakers.

Following the introduction of the study, the rest of the paper is organized as follows. Section “COVID-19, economy and energy markets” sheds lights on the relevant literature on the COVID-19 pandemic and its impact on the economy and energy markets. Section “Materials and methods” presents the empirical strategy to achieve the research objective, including data, methodology, and study variables. Section “Findings and discussions” discusses the empirical results, and finally, section “Conclusion and implications” concludes the study with practical and policy implications.
COVID-19, economy and energy markets

The COVID-19 pandemic is widely acknowledged to be an extreme public health event and an unprecedented economic shock. To address the impacts of this pandemic, quite a few studies focused on different aspects of the economy and markets. Studies have unanimously reported the negative effect of COVID-19 on economies across the globe. While there are works that have concentrated on a holistic economic impact, other researchers have examined the economic sector-wise effects of COVID-19.

Being a universal phenomenon, some studies have investigated the economic impact of COVID-19 from a global perspective, while others have undertaken either cross-country or single country analysis. The substantial effects of the pandemic thus prompted studies from different countries across all the continents. The research shows the devastating impact of the economies across different continents such as Asia, Europe, North America, Latin America, Oceania, and Africa. While the research demonstrates the damaging impact for the countries, emerging markets and developing economies faced additional challenges. Government restrictions on personal and economic activity had the most significant impact on global trade. Hence, the emerging economies experience unprecedented reversals in capital flows while coping with weaker health systems and more limited fiscal capacity to provide support.

In addition, a significant number of studies have shown the COVID-19 impacts on different sectors. Sectors like aviation and tourism experience a great shock with worldwide movement controls. The impact of COVID-19 has been addressed particularly from the perspectives of agriculture, education, labor market, and small and medium enterprises. An array of studies has focused on the effect of the COVID-19 pandemic in other sectors; however, the discussion is beyond the scope and interest of our research. Precisely, we highlight some recent literature since energy is one of the hardest-hit sectors across the globe due to critical fall in economic activities and movements of people and products.

One strand of research examines how the current pandemic is related to the energy market. For example, how the pandemic influences the energy price volatility is discussed by Devpura and Narayan. They study the evolution of hourly oil price volatility and find that volatility shot up following the onset of COVID-19. Wang and Su examines the asymmetric relationship between COVID-19 and fossil energy prices and reports that while the pandemic impacts oil and natural gas prices in high volatile quantiles, no causal relationship is established in the coal market. Another strand of research focuses on the impact of COVID-19 on energy firms. Fu and Shen, for instance, document that the performance of energy firms is negatively affected by COVID-19 in China. On the other hand, from the US perspective, Mazur et al. conclude heterogeneous reactions to COVID-19. It reveals that stocks in crude petroleum and oil services in the US experience substantial losses and the highest levels of volatility. Polemis and Soursou examine the pandemic’s impact on the stock returns of Greek energy listed companies and report that COVID-19 influences the returns of the majority of the listed firms.

Finally, the third group of studies focuses on renewables that were the only source that experienced a growing demand amid the pandemic. Czech and Wielechowski show that, compared to the conventional energy index, the alternative energy index stays in the low-volatility regime most of the time, without being significantly affected by the pandemic-related indicators. The findings reveal that the alternative energy sector is more resistant to COVID-19 than the conventional energy sector. Similarly, Corbet et al. assert that contrary to fossil fuels, investors during COVID-19 find alternative energy more reliable in generating long-term supply. However, Pradhan et al. contend that the effects of a pandemic on the global economy and fluctuation in
oil prices triggered its impact on the alternative energy industry. Chang et al.\textsuperscript{50} also observe risk spillovers from the conventional energy market to the renewable energy stock market.

The extant literature thus confirms that the COVID-19 pandemic has multidimensional effects on the economy and its different sectors as well as on the functioning of energy markets. While the literature shows the impacts of the pandemic on the economy or the energy markets in isolation, the current study envisages contributing by examining the dynamic nexus between these vital aspects during the ongoing crisis period. Besides, considering the availability of a relatively short span of the data period, we reasonably choose wavelet as our analytical tool. This method allows us to examine the relationship in the time horizon and the changes in different spell (frequency), unlike other methods used in the earlier studies. Therefore, the current study brings novelty and contributes to this evolving strand of research through a dynamic time–frequency analysis of economic activity and energy markets in a time of crisis.

\textbf{Materials and methods}

We employ wavelet decomposition analysis to investigate the dynamics between economic activity and energy markets during COVID-19. Wavelet is a useful analytical tool to help economic decision making by analyzing the economic correlation between variables based on the time horizon. The wavelet method allows overcoming the major deficiencies of the traditional time-series models by allowing decomposition of data into several time scales without imposing any assumptions on the return series and losing pertinent information.\textsuperscript{16} Notably, the method helps avoid heteroscedasticity bias, given that volatility should affect both low and high timescales correlations.\textsuperscript{18} Besides, decomposition of time-series data in the time and frequency domain is especially useful in dealing with signals which are non-stationary and portraying the changing frequencies over time, as we usually discover in financial data.\textsuperscript{18} Also, the decomposition method helps to detect structural breaks when a complete breakdown in correlation or a shift in the relevant frequency band occurs and provide analytical ground to identify the causal relationship at various frequencies.\textsuperscript{17} Moreover, analyzing data under the circumstances of a crisis uniquely help to detect unusual patterns—to give an overview of the dynamics of the relationship between couples of time series, allowing to localize and zoom in on particular patterns.\textsuperscript{51}

From a financial data analysis point of view, one notable advantage of the wavelet technique is that it can distinguish between short-term and long-term co-movement dynamics between sentiment and equity returns.\textsuperscript{51} The wavelet analysis is advantageous by classifying higher frequencies (i.e. investors’ sentiments, market integration, hedging, and speculative investors’ behaviors) and lower frequencies (fundamental factors).\textsuperscript{16} Particularly, by incorporating scale dependence, this method enables the researcher to identify unique portfolio diversification opportunities for different sets of investors bearing different investment horizons or holding periods of stocks (e.g. weekly, monthly, quarterly, etc.).\textsuperscript{52}

\textbf{Wavelet-based time–frequency analysis}

The wavelet method decomposes a time series as a wavelet function $\psi(t)$ that depends on the time parameter ($t$). It allows to decompose data in different components of the frequency and surveys each component in terms of resolution proportional to its scale.\textsuperscript{53} Hence, compared to conventional time-series analysis, this method helps to examine the relationship dynamics in the time domain and the frequency domain. For the wavelet decomposition, we follow the study of Grinsted et al.\textsuperscript{54} This approach captures the co-movement of return series in time–frequency space in the form of the
CWT, which is defined as the integral overall time of the signal multiplied by scaled, shifted versions of the wavelet function $\psi$. This can be generally represented as follows:

$$C(\text{scale, position}) = \int_{-\infty}^{\infty} x(t) \psi(\text{scale, position, } t) \, dt$$  \hspace{1cm} (1)

The results of the CWT are many wavelet coefficients $C$, which are a function of scale and position. The scale and position can take on any value compatible with the region of the time series, $x_t$. The CWT essentially plots the correlation of the time series in a two-dimensional figure (i.e. wavelet power spectrum), which allows easily identifying and interpreting patterns or hidden information.

We define the wavelet power spectrum as:

$$W_x(u, s) = |W_x(u, s)|^2$$  \hspace{1cm} (2)

This measures the relative variance of the time series at each time and on each scale. Similarly, we can define the cross-wavelet spectrum as:

$$W_{xy}(u, s) = W_x(u, s)\overline{W_y(u, s)}$$  \hspace{1cm} (3)

where $W_x(u, s)$ and $\overline{W_y(u, s)}$ are wavelet transforms of two time series $x(t)$ and $y(t)$. The cross-wavelet spectrum can be decomposed into real and imaginary parts. We define the cross-wavelet power as $|W_{xy}(u, s)|$, which depicts the local co-variance between two time series at each time and frequency. Moreover, the wavelet coherency power spectrum has the considerable benefit of being normalized correlation compared to cross-wavelet (which measures co-variance) of two series. We define the wavelet coherence following Torrence and Webster in Equation 4

$$R^2(u, s) = \frac{|S(s^{-1} W_{xy}(u, s))|^2}{S(s^{-1} |W_x(u, s)|^2) S(s^{-1} |W_y(u, s)|^2)}$$  \hspace{1cm} (4)

where $S$ is a smoothing operator over time as well as scale and $0 \leq R^2(u, s) \leq 1$. The value of $R^2(u, s)$ falls within a range between 0 and 1; the higher (lower) the value the stronger (weaker) is the co-movement of two series. Hence, the contour plot generated through the above measure allows us to recognize the regions and the degree of co-movement in both time and frequency space. The two time series move together and, specifically, assess both time- and frequency-varying features of the co-movement. For statistical inference, we rely on the Monte Carlo simulations.

However, wavelet squared coherence is restricted to positive and not distinguishable positive and negative correlations or co-movement. To solve the difficulty, we use the phase-difference approach suggested by Torrence and Compo, which helps us understand the positive and negative co-movements. This approach allows us to understand the causal relationships between the two time series commensurate with the Granger causality testing. The phase difference can be defined as:

$$\phi_{xy}(u, s) = \tan^{-1}\left(\frac{\text{Im}\{S(s^{-1} W_{xy}(u, s))\}}{\text{Re}\{S(s^{-1} W_{xy}(u, s))\}}\right)$$  \hspace{1cm} (5)

where $\text{Im}$ and $\text{Re}$ are the imaginary and real parts of the smoothed cross-wavelet transform, respectively. The information about the signs of each part is to determine the value of $\phi_{xy} \in [-\pi, \pi]$. Black arrows indicate phases on the wavelet coherence plots. A phase difference of zero means that the time series are moving together. On the contrary, when the arrows point towards the right (left), it indicates that time series are in-phase (out of phase), or the time series co-movement is positive (negative). Moreover, the relative position of the arrows specifies which variable is leading and which is lagging.
Data and variables

To measure the economic activities, we consider the daily return in the BDIR\(^2\), which is regarded as a leading indicator of global economic performances; the real global economic activities are reflected in the index.\(^{61-64}\) Besides, we use two sets of energy indices by Standard & Poor’s (S&P) to capture the movement in conventional and clean energy markets, namely, SPGER and SPGCER. The energy indices are major S&P market indices that consist of the businesses classified within the energy sector and clean energy production, equipment and technology companies\(^3\). Table 1 presents the descriptive statistics of the study variables, and Figure 1 shows their time-series graph.

The descriptive statistics in Table 1 and the lines graph in Figure 1 show the preliminary shreds of evidence of substantial market indices movement during analysis. Remarkably, the high standard deviation of the variables notifies the substantiation of high market volatility. Besides, Figure 1 illustrates the existence of co-movement of economic activities and energy markets. All three indices experienced a significant fall during the first quarter of 2020. To understand the volatility, co-movement, and causality robustly, we use wavelet methods described in the earlier section.

Our sample contains the daily data of the market indices from 1 January 2020, to 25 November 2020. Our data covers the period start of the pandemic and allows us to observe the changes along

| Variable | Obs. | Mean   | Std. Dev. | Min | Max  |
|----------|------|--------|-----------|-----|------|
| BDIR     | 236  | 1044.097 | 488.082   | 393 | 2097 |
| SPGER    | 236  | 1355.295 | 302.506   | 844.794 | 2101.397 |
| SPGCER   | 236  | 910.442  | 234.587   | 530.315 | 1471.038 |

Abbreviations: BDIR: Baltic Exchange Dry Index; SPGER: S&P Global 1200 Energy Index; SPGCER: S&P Global Clean Energy Index.

Figure 1. Time-series graph of the market indices.
the year. Hence, we essentially encompass critical phases of the COVID-19 crisis, from the human-to-human COVID-19 transmission confirmed on 21 January 2020, to the second wave of the pandemic delineated from early October 2020, at least partially. Data for three series is collected from Refinitiv Datastream. For the empirical analysis, following Jiang et al., we calculate the log-returns of the time-series data by finding the difference between two consecutive values as follows:

\[
 r_t = \ln \left( \frac{p_t}{p_{t-1}} \right)
\]  

Before moving to the wavelet-based analysis, we present the “White noise” properties of our variables under consideration. We present the test statistics of Bartlett’s Periodogram-based test for the presence of white noise in the residuals. We essentially test the null hypothesis (H0: Residual variable is white noise) for the existence of white noise. Figure 2 depicts the cumulative periodogram with blue color. The black solid lines on the both sides specify the 95%-confidence band for Bartlett’s test to prove that the time series is a white noise of constant mean and variance.

Bartlett’s test plot in Figure 2 is a test of the null hypothesis that the residual time series comes from a white-noise process of uncorrelated random variables having a constant mean and variance. Since the periodogram resides in the band, the residual time series is a white noise with a confidence level of at least 95% (also, the p-value > 0.05), thus we fail to reject the null hypothesis. Accordingly, we confirm the absence of serial correlation and heteroscedasticity; residuals are random and stationary.

**Findings and discussions**

**Market volatility during COVID-19**

The CWT plots for each variable are illustrated in Figure 2. The CWT presents the variance in the market index in the time scales and frequency bands. The horizontal and vertical axis of the graph demonstrates the time and frequency component of the analysis, respectively. The values range from scale 1 (a day) up to 64 (around three months). The statistical significance is measured
using the wavelet power against a null hypothesis of the stationary process with a background power spectrum. Using the phase randomized surrogate series estimated by Monte Carlo simulations, the 5% significance level is designated by the thick black regions against red noise.\textsuperscript{58} The cone of influence is displayed with a lighter shade signals distortion of the picture by edge effects. The range of power is from blue (low power) to red (high power). Table 2 provides the corresponding periods at 50 days interval shown in Figures 3 and 4.

In all three panels of Figure 3, we notice a high-volatility regime with the emergence of the COVID-19 pandemic worldwide. Specifically, the identical market volatilities started around 50 days period (early March 2020). Also, we notice that the markets remain volatile from higher frequency regions to lower frequency regions but at different degrees. All the indices remain significantly volatile in the shorter scale (high frequency), evidenced by the red hot zone in CWT plots for all three indices. Even though we notice some significant isolated zones, the market volatilities peaked in the earlier periods of the COVID-19 outbreak. The findings imply that the rapid rise of infection and death worldwide created major uncertainties in the economy and the energy markets.

Besides, the frequency dynamics of CWT indicate that shock generated in the economy and energy markets is long lasting. Even though the high volatility lasts in the market for around a week or so, the impact has not disappeared. As we can see, significant variances in the market return in the low-frequency band (scale 16–32) sustained for a more extended period than the high-frequency band. Specifically, the significant volatile region in the low-frequency band spread up to 100 days, that is, mid of May 2020. That indicates, the impact of COVID-19 induced crisis made a lasting impact on the economy and energy markets. The effect mostly smoothed out by the end of May onwards. However, we notice some isolated volatilities in the graphs, specifically for the BDIR and SPGER but inconsistently. The evidences suggest, the initial shock by the outbreak induced higher volatility. The findings are conceivable as the sudden fear due to the pandemic created more uncertainty in the economy and energy markets.

**Market co-movement and causal relationship**

It is essential to see the co-movement of time series, which may provide dynamic linkages between variables besides understanding individual market volatility. Accordingly, to comprehend the relative volatility further pertaining to the interactions between economic activities and selected energy market indices, we analyze wavelet coherences of each pair of variables, which is illustrated in Figure 4. The color indicates the level of correlation on the right side of the charts; the warmer the color (moving from cool (blue) to warm (red)), the higher the absolute correlation value for $R^2(\nu, s)$.

| Days in x-axis | Respective periods                  |
|---------------|-----------------------------------|
| 1–50          | 1st January–10th March            |
| 51–100        | 11th March–19th May               |
| 101–150       | 20th May–28th July                |
| 151–200       | 29th July–6th October             |
| 201 and above | 7th October–25th November         |
In Figure 4, we detect the existence of high dependence between economic activities and energy markets. Notably, Panel A indicates that co-movement between BDIR and SPGER remains strong during the entire analysis period and all frequency bands. On the other hand, unlike the conventional energy market, the clean energy market experiences a lesser degree of uncertainty, as evidenced by the Panel B wavelet coherency graph. The stronger association between BDIR and SPGER is plausibly related to the composition of the market indices. The conventional energy sector consists of many oil companies, which would suffer in a recession; hence, the oil price shock is likely to have additionally hurt these companies. Altogether, the high co-movement between economic activities and energy markets empirically validates the close relationship between economy and energy.

Furthermore, we detect the lead–lag relationship between the markets through the phase difference, which helps us to understand the nature of the relationship (i.e. positive or negative). Black arrows indicate phases on the wavelet coherence figures. Arrows pointing to the right show a positive correlation between the variables (in-phase), while the arrows pointing to the left imply a
A negative correlation between the variables (out-of-phase). Besides, if the arrows are horizontal (phase difference = zero), both variables move together towards the same direction but no lead–lag relationship. An arrow pointing downward-right or upward-left suggests that the first variable (i.e. BDIR) in the equation leads the second one (i.e. SPGER or SPGCER) and vice versa. Accordingly, we notice that the arrows are pointing to the right during the whole period of our analysis. The findings indicate the existence of a positive correlation between the BDIR and both energy market indices. However, we notice that the directions of the arrows do not remain static throughout the time; instead, we find that the lead–lag relationship changes between the variables. The dynamic changes are expected as energy indices respond to COVID-19 shock that varies over time due to fundamental, behavioral, and psychological factors.

Robustness test with wavelet-based causality analysis

To check the robustness of the CWT and WC analysis outcomes, we implement the wavelet-based Granger causality tests. The causality tests are implemented for six frequency domains (D1 to D6), and the results are presented in Table 3. Besides, we have presented the Granger causality results for the original data series at the end of Table 3 to comprehend the causal relationship among the variables.

From the results in Table 3, causality analysis gives us a mixed relationship dependent on the frequency domain. In the lower scale or D1–D2 (or high frequency), we find the relationship mostly remain statistically insignificant except for the causality running from SPGER to BDIR in the frequency domain of D1. This indicates the instant shock assumed by the energy sector made significant economic disruption instantaneously. On the other hand, in the medium-scale data (D3–D4), the clean energy market is mainly affected (SPGCER). The joint causal impact shows the dependence of the clean energy market on economic activities and the conventional energy market. However, the causal relationship changes markedly in the higher scale (D5–D6). Even though the causal relationship remains similar in the D5 frequency domain to D4; however, it shows substantial differences in the highest scale (D6). Thus, the causal relationships at this lower frequency domain are bi-directional.
The findings indicate that the shock in the economy and energy markets (conventional and clean) remains for a longer period, which may not be apparent in the short term. Also, the findings reveal the interdependence of energy sectors and economic activities. Thus, the findings indicate that those economic activities causing changes in both energy markets while the conventional energy markets Granger causes the changes in clean energy markets further.49 The comparative findings show that if we do not consider the causal movement at different timescales, it may hinder appropriate policy measures. In other words, the conventional causality relationship (original) suggests we focus only on the policy from the economic activities perspective. In contrast, policy interventions are needed in the energy markets in a practical sense, uncovered through our wavelet-based time–frequency analysis in the earlier section and substantiated with the wavelet-based Granger causality analysis (D1–D6). Accordingly, suitable policy synchronization can help to fight against the crisis more competently.

Conclusion and implications
This study provides strong evidence that the COVID-19 stimulated economic shocks exert substantial adverse effects on energy markets. Specifically, we provide findings on market dynamics from the perspectives of both conventional and clean energy markets. Our wavelet-based dynamic time–

| Wavelet scale | Dependent variable | Independent variables |
|---------------|--------------------|-----------------------|
| D1            | BDIR               | —                     |
|               | SPGER              | 9.513**               |
|               | SPGCER             | 6.938                 |
| D2            | BDIR               | —                     |
|               | SPGER              | 6.321                 |
|               | SPGCER             | 5.075                 |
| D3            | BDIR               | —                     |
|               | SPGER              | 7.002                 |
|               | SPGCER             | 5.075                 |
| D4            | BDIR               | —                     |
|               | SPGER              | 6.333                 |
|               | SPGCER             | 7.303                 |
| D5            | BDIR               | —                     |
|               | SPGER              | 7.450                 |
|               | SPGCER             | 7.482                 |
| D6            | BDIR               | —                     |
|               | SPGER              | 3.527                 |
|               | SPGCER             | 10.132**              |
| Original      | BDIR               | —                     |
|               | SPGER              | 49.544***             |
|               | SPGCER             | 36.443***             |

Notes: Asymptotic chi-square values are reported. ***, **, and * are significant value at 1% significant value, 5%, significant value, and 10% significant value.

Abbreviations: BDIR: Baltic Exchange Dry Index; SPGER: S&P Global 1200 Energy Index; SPGCER: S&P Global Clean Energy Index.
frequency analysis finds that the conventional energy market is hit harder than the clean energy markets. Given the importance of the growing pandemic of COVID-19, our findings have important implications for policymakers and investors holding assets in international energy markets.

To bring and maintain stability in the energy markets, enhanced cooperation between the governments, particularly the influential energy market players are essential. The recent oil price war between OPEC and Russia worsened the situation in the wake of the COVID-19 pandemic. Avoiding such geopolitical uncertainties would help lessen the impact on the energy markets while the economy is already in great shock. Also, given the immediate crisis, governments are attentively concentrating on managing the COVID-19 pandemic and mitigating the effects on economies. However, such diversion of focus could have severe unintended consequences for the low-carbon energy transition. The investors holding assets for different energy stocks can find our results useful for the price prediction. Notably, our findings at a different time–frequency would help investors buy and hold energy stocks by understanding the impact at a different scale or duration. However, considering the relatively shorter data period, we recommend drawing conclusions cautiously from our findings. Although our empirical results are helpful in comprehending and implementing instant policy changes needed to tackle crunches in energy markets and the economy, devising policies for the long term requires further ex-post evaluation once the pandemic is over.

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Notes
1. “An updated assessment of the economic impact of COVID-19” by Asian Development Bank (ADB). Available at: https://www.adb.org/publications/updated-assessment-economic-impact-covid-19.
2. The Baltic Dry Index measures the cost of shipping goods around the world which is reported daily by the Baltic Exchange in London. The index offers a benchmark for the price of the transportation of the major raw materials by sea (tradingeconomics.com).
3. S&P Dow Jones market indices website. Available at: https://www.spglobal.com/spdji/en/.
4. Considering five trading days in a week.

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