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How to mitigate climate change? Dynamic linkages between clean energy and systemically important banks

Zhiqiang Tong[1,2], Yijiu Ding[3], Shenglin Ma[4]* and Han Yan[5]*

[1]Department of Accounting, Guangxi Technology and Business Vocational College, Nanning, China
[2]Infrastructure University Kuala Lumpur, Kajang, Selangor, Malaysia
[3]School of International Business. Shandong Vocational University of Foreign Affairs, Weihai, China
[4]School of Economics and Management, North University of China, Taiyuan, China
[5]School of Accountancy, Hebei University of Economics and Business, Shijiazhuang, China
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*to whom all correspondence should be addressed: e-mail: sz202209002@st.nuc.edu.cn
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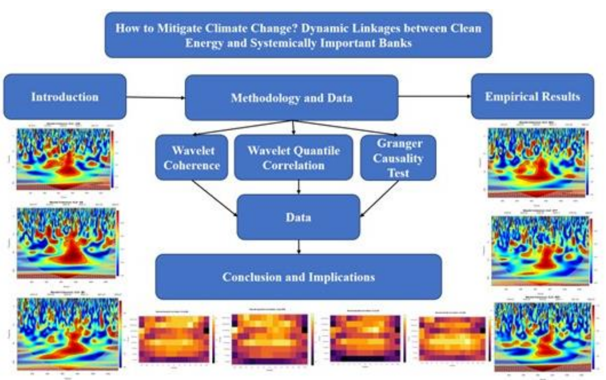
Graphical abstract



Abstract

This study employs wavelet coherence, wavelet quantile correlation, and Granger causality tests to comprehensively investigate the dynamic correlation characteristics between the U.S. clean energies and the stock returns of seven systematically important banks (SIBs). The main findings are as follows: (1) Granger causality tests indicate that theclean energies has significant predictive power for the stock returns of all SIBs, with the most significant effects on State Street Corporation (F=7.3147) and Morgan Stanley (F=7.1673); (2) Wavelet coherence analysis reveals significant time-frequency domain features, with high-frequency intermittent correlations in the short term, stable correlation patterns in the medium term, and a large-scale high-correlation region formed from late 2019 to 2020 in the long term; (3) Wavelet quantile correlation analysis finds that the medium quantile range (0.3-0.7) maintains a stable positive correlation, while the extreme quantile regions exhibit significant attenuation or negative correlation, with this asymmetric feature being particularly evident in Goldman Sachs and Wells Fargo; (4) Time-varying feature analysis shows a structural weakening of market linkages after 2021, reflecting adjustments in financial institutions' investment strategies in the post-COVID-19 period. The research findings have important implications for financial regulation and investment decision-making.

Keywords: Clean energies; systemically important banks; wavelet coherence; quantile correlation; time-frequency analysis

JEL Classification: G21; G32; Q42; C14; C58

1. Introduction

Developing clean energy has become a consensus and inevitable choice for countries worldwide in the face of increasingly severe global climate change and environmental pollution problems (Xu and Lin, 2024; Yang and Zhan, 2024; Dirie *et al*., 2024). Clean energy not only helps to reduce greenhouse gas emissions and improve environmental quality, but also promotes sustainable economic development and ensures energy security (Zhang, 2008; Qamruzzaman and Karim, 2024; Karpavicius *et al*., 2024). In recent years, under policy support and market-driven forces, the global clean energy industry has developed vigorously, showing a positive trend of expanding investment scale, increasing technological level, and gradually widening application fields (Quitzow *et al*., 2015; Armstrong *et al*., 2016; Pan and Dong, 2023).

As the world's largest economy and energy consumer, the United States plays a crucial role in the development of clean energy (Zeng *et al*., 2024 ; Ma *et al*.,2024). The U.S. government attaches great importance to clean energy and has introduced a series of policy measures to support industrial development, such as the Clean Energy Act and the Climate Change Solutions Act (Wang and Ma,2024). These measures have significantly increased the application ratio of clean energy in fields such as electricity and transportation, promoting the low-carbon transformation of the energy structure (Kumar *et al*., 2023; Zeng, 2024; Wu *et al*., 2025). Driven by policy benefits and market opportunities, the U.S. clean energy industry has rapidly risen and gradually become an important force leading the global clean energy revolution (Li *et al*.,2024).

The vigorous development of the clean energy industry is inseparable from financial support. Enterprises require a large amount of capital investment in technology research and development, project construction, and equipment manufacturing. Therefore, the connection between industrial development and financial markets is becoming increasingly close (Qadir *et al*., 2021; Krishnan *et al*., 2022; Gollakota and Shu, 2023; Zeng *et al*., 2024). On the one hand, listed companies raise funds through the capital market, and stock performance directly affects corporate financing capabilities. The fluctuation of the clean energies reflects the overall trend of the industry (Henriques and Sadorsky, 2008; Ferrer *et al*., 2018; Zeng *et al*., 2025). On the other hand, banks support clean energy projects through green credit, and their loan allocation and risk exposure are closely related to industrial development (Lu and Zeng, 2023; Zeng *et al*., 2025). As clean energy is mostly a capital-intensive industry, the capital supply status of the banking system largely determines the speed and quality of industrial development.

The banking industry is the core of the financial system and plays an irreplaceable role in supporting the real economy and maintaining financial stability (Wen *et al*.,2024). The 2008 global financial crisis exposed the vulnerability of systemically important financial institutions, triggering high attention from regulatory authorities in various countries to systemic risks (Weiß *et al*., 2014; Calluzzo and Dong, 2015; Zeng *et al*., 2023; Wu *et al*., 2024). Systemically important banks (SIBs), due to their large scale, high interconnectedness, and complex business characteristics, are closely linked to financial stability and the real economy. Once in distress, they are highly likely to trigger systemic risks and endanger financial and even economic stability. Therefore, accurately understanding the shocks and risks faced by SIBs is crucial (Drehmann and Tarashev, 2013; Cai *et al*., 2018; Tharun *et al*., 2023).

With the rapid development of the U.S. clean energy industry, the demand for bank credit from related enterprises is becoming increasingly strong. Banks vigorously support industrial development through measures such as issuing green loans, and the correlation between credit assets and the clean energy industry is continuously increasing (Sen and Ganguly, 2017; Wu *et al*., 2024). This deep integration is beneficial for banks to optimize their credit structure and broaden their business scope (Lu *et al*., 2023; Abedin *et al*., 2024). However, on the other hand, industrial fluctuations may also affect banks' asset quality and profitability, thereby damaging the banking system and even financial stability (Acharya and Ryan, 2016). Particularly for SIBs that occupy a core position in the financial system, their risk exposure to the clean energy industry deserves more attention.

In summary, under the background of the global economic green and low-carbon transformation, accurately grasping the relationship between the development of the clean energy industry and the stability of the banking industry is crucial. This not only concerns the healthy growth of the industry and the sound operation of the banking system, but also relates to the smooth operation of the entire financial and even economic system. However, existing literature has rarely explored the relationship between the U.S clean energies and the returns of SIBs from the perspective of time-frequency domain and quantile regression, especially the tail correlation under extreme market conditions needs further examination, and the causal relationship between the two also needs to be clarified.

In view of this, this study intends to fill this research gap by adopting econometric methods such as wavelet estimation, quantile regression, and Granger causality checks, in order to provide new perspectives and empirical support for correctly understanding and effectively preventing and controlling related risks. The methodology adopted in this study has the following main advantages: (1) Through wavelet coherence analysis, accurate capture of time-frequency domain characteristics is realized. This method can not only consider the time domain and frequency domain information simultaneously, but also reveal the dynamic evolution process of market linkage, overcoming the limitations of traditional time series methods that are difficult to identify different frequency characteristics; (2) Innovatively introducing wavelet quantile correlation analysis, this method can effectively characterize the correlation characteristics at different quantile levels, especially the tail correlation under extreme market conditions, which can provide richer and more accurate information than traditional correlation analysis methods; (3) Using Granger causality tests to strictly test the lead-lag relationship between variables, and ensuring the reliability of the causal relationship judgment through robustness tests of multiple lag orders. The complementary use of the three methods constructs a multi-dimensional analysis framework that can comprehensively characterize market linkage from multiple aspects such as time-frequency characteristics, non-linear characteristics, and causal relationships, improving the reliability and completeness of the research conclusions.

The contributions of this paper to the existing work are mainly reflected in the following aspects: (1) Innovatively introducing time-frequency analysis methods into the research field of clean energy and financial stability, and through wavelet coherence analysis, for the first time revealing the dynamic correlation characteristics of theclean energies and the stock returns of SIBs at different time scales, providing a new analytical perspective for understanding the interaction mechanism between the two markets; (2) Using the wavelet quantile correlation method, for the first time systematically examining the non-linear correlation characteristics of clean energy and bank stock returns under different market conditions, discovering significant asymmetric effects, especially the important finding that the clean energy sector may have a risk diversification role under extreme market conditions; (3) Based on multi-dimensional empirical analysis, deeply discussing the correlation differences between banks with different business models and the clean energy market, revealing the characteristics that asset management banks show the strongest correlation, while comprehensive commercial banks are relatively weaker, providing new evidence for understanding the impact of financial institutions' business models on market risk exposure; (4) Systematically examining the structural changes in market linkage after 2021, discovering new characteristics of financial institutions' investment strategy adjustments in the post-COVID-19 period, which has important implications for understanding the evolution mechanism of market correlation under major external shocks; (5) Based on the research findings, proposing targeted policy recommendations, including incorporating clean energy market fluctuations into the systemic risk assessment framework, optimizing banks' credit structure and risk management strategies, etc., providing practical guidance for regulatory authorities and market participants. These contributions not only fill the gaps in existing research, but also provide important references for theoretical development and practical application in related fields.

Through empirical research, this study obtains the following main findings: (1) Granger causality tests show that theclean energies has significant predictive power for the stock returns of all SIBs, with the most significant effects on State Street Corporation (F=7.3147) and Morgan Stanley (F=7.1673), while the predictive effect on Goldman Sachs Group (F=6.3641) is relatively weaker, reflecting the significant differences in the degree of correlation between banks with different business models and the clean energy market; (2) Wavelet coherence analysis reveals significant time-frequency domain characteristics, that is, high-frequency and intermittent correlations in the short term (4-16 days), more continuous and stable correlation patterns in the medium term (16-64 days), and the most significant and persistent correlations in the long term (64-256 days), especially the formation of a large-scale high-correlation region from late 2019 to 2020, reflecting the systemic risk impact during COVID-19; (3) Wavelet quantile correlation analysis finds significant non-linear characteristics, manifested as a stable positive correlation with each bank in the medium quantile range (0.3-0.7), while the correlation in the extreme quantile regions shows significant attenuation or turns negative, with this asymmetric feature being particularly evident in Goldman Sachs and Wells Fargo, suggesting that the clean energy sector has a risk diversification role under extreme market conditions; (4) Time-varying feature analysis shows that after 2021, market linkage undergoes structural changes, with all frequency domains experiencing a weakening of correlation intensity, reflecting the adoption of more prudent and differentiated investment strategies by financial institutions in the post-COVID-19 period; (5) From the perspective of industry differences, asset management banks show the strongest correlation, followed by investment banks, while comprehensive commercial banks show a medium level of correlation, reflecting the significant differences in the impact of different business models on clean energy market exposure. These findings not only enrich relevant theoretical research, but also provide important practical guidance for financial regulation and investment decision-making.

2. Methodology and data

2.1. Wavelet coherence

The Wavelet Transformation Coherence (WTC) technique allowed economists to investigate the time-based connections between various financial industries during different historical periods (Torrence and Compo, 1998). By analysing data series that had been temporally smoothed, statistical correlation metrics were obtained across time scales. These statistical covariance measures, represented by mathematical symbols, revealed how chronological data interacted at specific points and frequencies. Subsequently, equations were developed to mathematically express the power spectrum analysis of two time series.

$$W_n^{XY}(s) = W_n^{X}(s) W_n^{*Y}(s) \tag{1}$$

Where, $W_n^X(S)$ and $W_n^{*Y}(S)$ are used for two assets of continuous wavelet transforms. S denotes the complex conjugate. The phase of the WTC is showed by.

$$\varnothing_n^{XY} S = \tan^{-1}\left(\frac{In\left\{S\left(S^{-1}W_n^{XY}(s)\right)\right\}}{Re\left\{S\left(S^{-1}W_n^{XY}(s)\right)\right\}}\right) \tag{2}$$

where *In* and *Re* are the imaginary and actual sections of the smoothed power spectrum.

2.2. Wavelet quantile correlation

Kumar and Padakandla (2022) extended the transformation of conventional QC analysis into an innovative WQC approach. Their groundbreaking methodology facilitated a more precise examination of bilateral financial instrument relationships. $Q_{\tau,X}$ response to the τ^{th} quantile of X, and $Q_{\tau,Y}(X)$ is with the τ^{th} quantile of Y, assume that X as the precondition. Then, it is focus on that X structure is independent.

Quantile covariance is given as,

$$where\ 0<\tau<1 \qquad \varphi_\tau(w) = \tau - I(w<0) \tag{3}$$

The QC,

$$qcov_t(Y,X) = \frac{qcov_t(Y,X)}{\sqrt{\left(var\left(\varphi_\tau\left(Y-Q_{\tau,Y}\right)var(X)\right.\right.}} \tag{4}$$

Kumar and Padakandla (2022) introduced the QC method by combined a maximal overlapping discrete wavelet transform to decompose assets X_t, and Y_t. Then they decompose the pairs X_t, and Y_t at level j^{th}, applying individual methods to estimate the WQC for each degree j So the estimation of WQC by Kumar and Padakandla (2022) is:

$$WQC_{\tau}\left(d_j[X],d_j[Y]\right)=\frac{q\text{cov}_{\tau}\left(d_j[Y],d_j[X]\right)}{\sqrt{\text{var}\left(\phi_{\tau}\left(d_j[Y]-Q_{\tau,d_j[Y]}\right)\right)\text{var}\left(d_j[X]\right)}} \quad (5)$$

where X, and Y point out the independent and dependent assets, respectively.

2.3. Granger causality test

The unrestricted model, representing our alternative hypothesis, can be expressed as:

$$Y_t=\alpha_0+\sum_{i=1}^{p}\alpha_i Y_{t-i}+\sum_{j=1}^{p}\beta_j \text{Clean Energy}_{t-j}+\varepsilon_t \quad (6)$$

where Y_t represents the bank stock return at time t, Clean Energy denotes the Clean Energy return at time t, p signifies the optimal lag length determined through information criteria, and ε_t represents the error term. The coefficients α_i and β_j are parameters to be estimated.

Algorithm 1 Dynamic Linkages between Clean Energy and Systemically Important Banks

Part 1: Wavelet Coherence (WTC) Analysis
Require: Time series data for clean energy returns and bank stock returns
Ensure: Wavelet coherence measures across time scales
Perform continuous wavelet transform on clean energy returns to obtain $W_X(s)$
Perform continuous wavelet transform on bank stock returns to obtain $W_Y(s)$
Calculate cross-wavelet transform: $W_{XY}(s)=W_X(s)W_Y^*(s)$
Compute wavelet coherence: $R_{XY}^2(s)=\frac{|S(s^{-1}W_{XY}(s))|^2}{S(s^{-1}|W_X(s)|^2)S(s^{-1}|W_Y(s)|^2)}$
Calculate phase difference: $\phi_{XY}(s)=\tan^{-1}\left(\frac{\mathcal{I}m(S(s^{-1}W_{XY}(s)))}{\mathcal{R}e(S(s^{-1}W_{XY}(s)))}\right)$
Part 2: Wavelet Quantile Correlation (WQC) Analysis
Require: Time series data for clean energy returns and bank stock returns, quantile levels τ
Ensure: Wavelet quantile correlation measures at different scales and quantiles
Apply maximal overlapping discrete wavelet transform to clean energy returns to decompose into $d_j[X]$
Apply maximal overlapping discrete wavelet transform to bank stock returns to decompose into $d_j[Y]$
for each wavelet scale j **do**
  for each quantile level τ **do**
    Calculate quantile $Q_\tau(d_j[X])$ and $Q_\tau(d_j[Y])$
    Compute quantile covariance:
    $qcov_\tau(d_j[X],d_j[Y])=\mathbb{E}[\phi_\tau(d_j[Y]-Q_\tau(d_j[Y]))(d_j[X]-\mathbb{E}(d_j[X]))]$
    Calculate wavelet quantile correlation:
    $WQC_\tau(d_j[X],d_j[Y])=\frac{qcov_\tau(d_j[X],d_j[Y])}{\sqrt{var(d_j[X])q_{var_\tau}(d_j[Y],d_j[Y])}}$
  end for
end for
Part 3: Granger Causality Test Implementation
Require: Time series data for bank stock returns Y_t and clean energy returns Clean Energy_t
Ensure: Granger causality test results
Check stationarity of time series using unit root tests
if series are non-stationary **then**
  Apply appropriate transformations (differencing)
  Check for cointegrating relationships
end if
Determine optimal lag length p using AIC or BIC information criteria
Estimate unrestricted model:
$Y_t=\alpha_0+\sum_{i=1}^{p}\alpha_i Y_{t-i}+\sum_{j=1}^{p}\beta_j\text{Clean Energy}_{t-j}+\varepsilon_t$
Estimate restricted model:
$Y_t=\alpha_0+\sum_{i=1}^{p}\alpha_i Y_{t-i}+\varepsilon_t$
Calculate residual sum of squares: RSS_R and RSS_{UR}
Compute F-statistic: $F=\frac{(RSS_R-RSS_{UR})/p}{RSS_{UR}/(T-2p-1)}$
Test null hypothesis $H_0:\beta_1=\beta_2=...=\beta_p=0$
if p-value ¡ significance level **then** [1]
  Conclude clean energy Granger-causes bank stock returns
else
  Conclude no Granger causality from clean energy to bank stocks
end if
return Comprehensive analysis results including WTC, WQC, and Granger causality metrics

The restricted model, corresponding to our null hypothesis, excludes the Clean Energy variables and takes the form:

$$Y_t=\alpha_0+\sum_{i=1}^{p}\alpha_i Y_{t-i}+\varepsilon_t \quad (7)$$

Our null hypothesis posits that CLG does not Granger-cause bank stock returns, which mathematically translates to:

$$H_0:\beta_1=\beta_2=\cdots=\beta_p=0 \quad (8)$$

The alternative hypothesis suggests that at least one β_j differs from zero, indicating Granger causality from Clean Energy to bank stock returns.

To test these hypotheses, we employ an F-statistic constructed as:

$$F=\frac{\left(RSS_R-RSS_{UR}\right)/p}{RSS_{UR}/\left(T-2p-1\right)} \quad (9)$$

where RSS_R and RSS_{UR} represent the residual sum of squares from the restricted and unrestricted models respectively, T denotes the number of observations, and p represents the lag length.

The implementation requires careful consideration of several econometric issues. First, the selection of optimal lag length utilises information criteria such as AIC or BIC. Second, we ensure the stationarity of all time series through appropriate unit root tests and transformations if necessary. Third, when dealing with non-stationary series, we examine potential cointegrating relationships between Clean Energy and bank stocks.

The decision rule relies on the comparison of the calculated F-statistic with critical values at conventional significance levels. When the p-value associated with the F-statistic falls below the chosen significance level (typically 0.05), we reject the null hypothesis, providing statistical evidence that Clean Energy Granger-causes the respective bank stock returns.

This analysis framework enables us to quantify the predictive relationship between Clean Energy and major US bank stocks, contributing to our understanding of information transmission mechanisms in financial markets. Algorithm 1 provides pseudo-code for the methods we use.

2.4. Data

The data for this study were obtained from Refinitiv Datastream, a comprehensive financial database accessible through institutional subscription. Our dataset covers the daily trading data spanning from January 1, 2017, to January 1, 2023. The research sample includes the stock price data of the US Wilderclean energies (CLG) and seven major US systemically important banks identified by the Financial Stability Board: Morgan Stanley (MS), JPMorgan Chase (JPM), Goldman Sachs Group (GS), Bank of New York Mellon (BK), Bank of America (BAC), State Street Corporation (STT), and Wells Fargo (WFC). These financial institutions were selected based on their systemic importance to the US financial system and global economy. For each entity, we collected daily closing prices data using Datastream's specific identifiers. To ensure data quality and reliability, we performed necessary preprocessing on the raw data, including removing trading days with abnormal trading volumes (defined as those exceeding three standard deviations from the mean). All price series were log-differenced to obtain return series. The complete dataset, is available upon reasonable request to the corresponding author, according to Refinitiv and University's data usage policies.

3. Empirical results

Table 1 presents the descriptive statistics of the data used in this study, revealing several significant characteristics. Firstly, the mean value of CLG is 0.06, which is notably higher than the mean values of other financial institution stocks (around 0.001). This suggests that the clean energies exhibited a better overall growth trend during the sample period. The average returns of other financial institution stocks are relatively close, all maintaining at a low level.

In terms of volatility, the variance of CLG is 6.414, significantly higher than the levels of other financial institution stocks (around 0.001). This indicates that the clean energies has a markedly greater volatility, reflecting the higher uncertainty and risks that the clean energy market may face.

Regarding skewness, CLG shows a clear negative skewness (-0.473), indicating that its return distribution is skewed to the left, with more extreme negative returns occurring. Similarly, BK (-0.555), STT (-0.374), and WFC (-0.484) also exhibit significant negative skewness, reflecting that these bank stocks may have experienced some notable downward events during the sample period. In contrast, the slight positive skewness of MS (0.073) suggests that it may have had more small-scale upward movements.

The kurtosis data show that all variables have a kurtosis greater than 3 (the kurtosis of a normal distribution), especially JPM with a kurtosis as high as 13.995 and MS with 13.161. This indicates that the return distributions of these financial stocks exhibit a "sharp peak and heavy tail" feature, with extreme returns occurring more frequently than in a normal distribution. The kurtosis of CLG is relatively lower at 4.954, suggesting that its extreme returns occur less frequently.

Table 1. Descriptive statistics

	CLG	MS	JPM	GS	BK	BAC	STT	WFC
Mean	0.06	0.001	0.001	0.001	0.001	0.001	0.001	0.001
Variance	6.414	0.001	0.001	0.001	0.001	0.001	0.001	0.001
Skewness	-0.473	0.073	-0.104	-0.151	-0.555	-0.058	-0.374	-0.484
	0	-0.271	-0.119	-0.025	0	-0.383	0	0
Kurtosis	4.954	13.161	13.995	9.98	11.544	11.303	12.346	9.17
JB	1417.056***	9650.753***	10914.058***	5553.180***	7493.116***	7117.829***	8522.712***	4737.132***
ERS	-9.669***	-10.583***	-10.225***	-12.099***	-7.979***	-9.405***	-12.187***	-8.334***

*Notes: JB represents the Jarque-Bera test, ERS represents the Elliott-Rothenberg-Stock unit root test, and * * * is significant at the 1% significance level*

Table 2. The Granger causality test of clean energy for systemically important US banks

Variable	CLG → Specify Bank (F statistics)
MS	7.1673
JPM	6.942
GS	6.3641
BK	6.7045
BAC	6.8745
STT	7.3147
WFC	6.9705

Note: All tests used order 2 lag with degrees of freedom (2,1331). An F statistic greater than 3 indicates significant at the 5% level

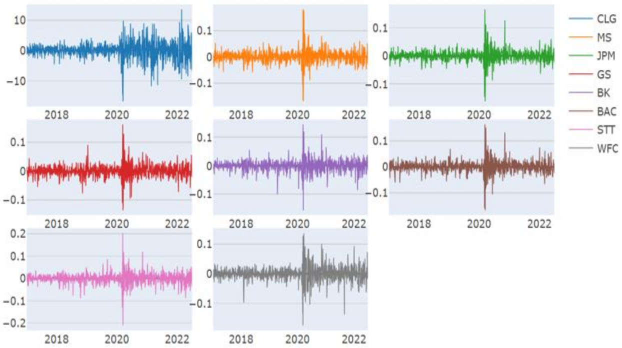


Figure 1. Daily time series trends

The Jarque-Bera (JB) test results show that the statistics of all variables are highly significant (marked with ***), further confirming that the return series significantly deviate from the normal distribution. Among them, JPM has the highest JB statistic (10914.058), indicating that its return distribution deviates the most from the normal distribution.

Finally, the ERS unit root test results are statistically significant (either *** or * marked) for all variables, indicating that all time series are stationary. This provides a reliable statistical foundation for subsequent time series analyses, such as the Granger causality test.

Figure 1 presents the time series plot of daily returns for CLG and the seven systemically important banks from 2018 to 2022. During this observation period, the fluctuation range of CLG is significantly larger than that of other bank stocks, especially during the COVID-19 period in 2020, when all series experienced a significant increase in volatility. The fluctuation range of CLG is between -10% and 10%, while the fluctuation range of bank stocks is generally between -0.1% and 0.1%. This figure intuitively reflects the higher volatility characteristics of the clean energy market compared to traditional bank stocks, and also demonstrates the common impact of systemic risk events on both markets.

According to the results of the Granger causality test in **Table 2**, the CLG has a significant leading role in indicating bank stock prices, revealing an interesting pattern of financial market linkage.

From the test results, CLG has the most significant impact on MS, with an F-statistic reaching 7.1673, suggesting that fluctuations in the clean energy industry may influence the performance of Morgan Stanley's investment banking business in advance. This relationship may stem from Morgan Stanley's deep involvement in clean energy project financing and related financial services.

For JPMorgan Chase (JPM) and Wells Fargo (WFC), CLG also exhibits a strong Granger causality relationship, with F-statistics of 6.9420 and 6.9705, respectively. This indicates that the business of these two large commercial banks may be closely related to the development trends of the clean energy industry, especially in areas such as project loans and green bond underwriting.

Bank of America (BAC) and Bank of New York Mellon (BK) also exhibit similar patterns, with F-statistics of 6.8745 and 6.7045, respectively. This relationship may reflect the important financial intermediary role played by these banks in the clean energy transition process, including providing financing support and consulting services for renewable energy projects.

State Street Corporation (STT) shows the strongest influenced relationship, with an F-statistic as high as 7.3147. This may be because State Street Corporation, as an important asset management and custody bank, has business performance that is more easily affected by investment trends in the clean energy industry. Its large number of ETF and index fund products may contain a substantial amount of clean energy-related assets.

Although Goldman Sachs (GS) also exhibits a significant causal relationship (F-statistic of 6.3641), it is relatively weaker. This may indicate that Goldman Sachs' business model is relatively more diversified and less dependent on a single industry, but it still cannot completely avoid the impact of clean energy market fluctuations.

This widespread leading relationship suggests that the development of the clean energy market has become an important factor influencing the performance of financial institutions. As the global energy transition progresses, this impact may further strengthen. Financial institutions may need to consider the development trends of the clean energy market more when formulating strategies and risk management policies. This also provides an important market signal for investors: changes in theclean energies may be used to predict the trend of bank stocks.

Figure 2 shows the time-frequency linkage between the CLG and JPMorgan Chase (JPM). In the short-run frequency domain (4-16 days), CLG and JPM exhibit relatively frequent intermittent correlations. This correlation appears throughout the sample period but varies in strength, with several significant high-correlation regions emerging particularly in mid-2019 and early 2020. The arrow directions show that there is a bidirectional lead-lag relationship between the two markets during these periods, indicating a complex mechanism of mutual influence between the two markets in the short term.

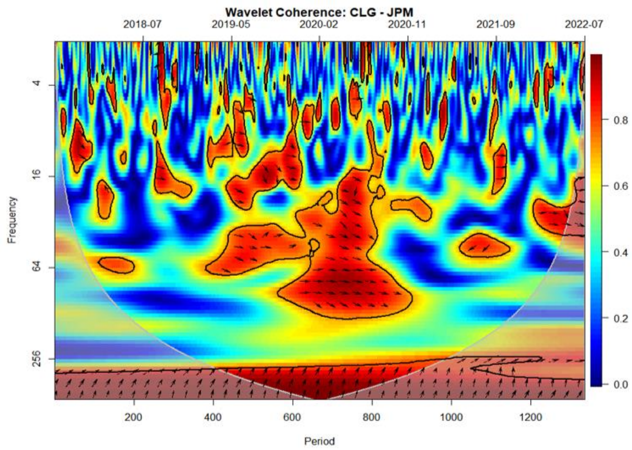


Figure 2. Time-frequency linkage relationship between the CLG and JP Morgan (JPM)

In the medium-term frequency domain (16-64 days), we observe a more significant and sustained correlation pattern. Notably, from late 2019 to mid-2020, a large-scale high-correlation region emerges, coinciding with the global spread of the COVID-19 crisis. During this period, the arrows mainly point to the lower right, indicating that JPMorgan's market movements lead theclean energies, which may reflect that financial institutions' market reactions are faster than the clean energy sector under the impact of COVID-19.

In the long-term frequency domain (64-256 days), the two markets exhibit the most stable and strong correlations. From late 2019 until the end of 2020, we observe a significant large-scale red region, indicating a sustained strong correlation between the two markets during this period. The arrow direction is generally consistent, pointing to the right, showing that the two markets maintain synchronous movements in the long run. This phenomenon may reflect the common influence of systemic risks and overall market sentiment in global financial markets during COVID-19.

It is particularly noteworthy that from the second half of 2020 to early 2021, we observe a weakening of correlations across multiple frequency domains. This may be related to the gradual return of the market to normal after COVID-19 and the emergence of differentiated trends in different sectors. By the end of 2021 and early

2022, correlations strengthen again in the short-run and medium-term frequencies, which may be related to the global economic recovery and the advancement of energy transition policies.

Figure 3 explores the correlation strength and lead-lag relationship between the CLG and Goldman Sachs (GS) in different frequency domains.

In the short-run frequency domain (4-16 days), CLG and GS exhibit high-frequency and intermittent correlation characteristics. This correlation repeatedly appears throughout the study period but varies in strength and duration. Notably, several significant high-correlation regions emerge in the second quarter of 2019 and early 2020. The arrow directions within these regions show alternating lead-lag relationships between the two markets in the short term, reflecting the bidirectional nature of market information transmission.

The medium-term frequency domain (16-64 days) reveals a more sustained and stable correlation pattern. Particularly from late 2019 to mid-2020, a significant high-correlation region is formed. During this period, the arrows mainly point to the right and slightly downward, indicating that Goldman Sachs' market fluctuations slightly lead theclean energies. This phenomenon may stem from the higher sensitivity of traditional financial institutions to market shocks compared to the emerging clean energy sector during the global COVID-19 outbreak.

In the long-term frequency domain (64-256 days), the two markets exhibit the most significant linkage. Starting from the fourth quarter of 2019 and extending to the end of 2020, we observe a large-scale red high-correlation region. The arrow direction during this period is relatively consistent, pointing to the right, suggesting that the two markets maintain synchronous movements in the long run. This phenomenon likely reflects the common systemic risks faced by global financial markets during COVID-19 and the overall consistency of investor sentiment.

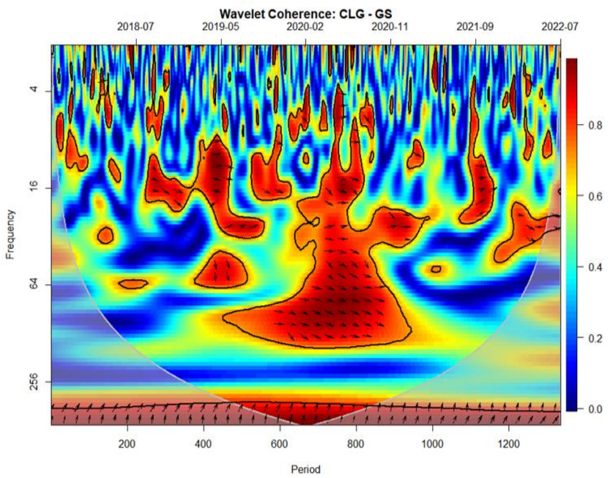


Figure 3. Correlation strength and lead-lag relationship between the CLG and Goldman Sachs (GS) in different frequency domains

Entering 2021, we notice significant changes in correlations across all frequency domains. In the first half of 2021, correlations generally show a weakening trend, which may be related to the differentiated recovery paces of different industries in the post-COVID-19 era. However, in the fourth quarter of 2021, new high-correlation regions emerge in the short-run and medium-term frequency domains, which may be related to financial institutions' strategic adjustments to clean energy transitions during the global economic recovery process.

Data from the first half of 2022 show new characteristics in the correlation between the two markets. Correlations in the short-run frequency domain become more frequent but weaker in strength, while the medium-term frequency domain maintains a relatively stable correlation of moderate strength. This change may reflect the balance between the market's long-term expectations for clean energy transitions and short-run market fluctuations.

Overall, the correlation between CLG and GS exhibits significant time-varying characteristics and unique interaction patterns at different time scales. This complex dynamic relationship not only reflects the deep connection between traditional financial institutions and emerging energy markets but also highlights the profound impact of major external events on market linkages.

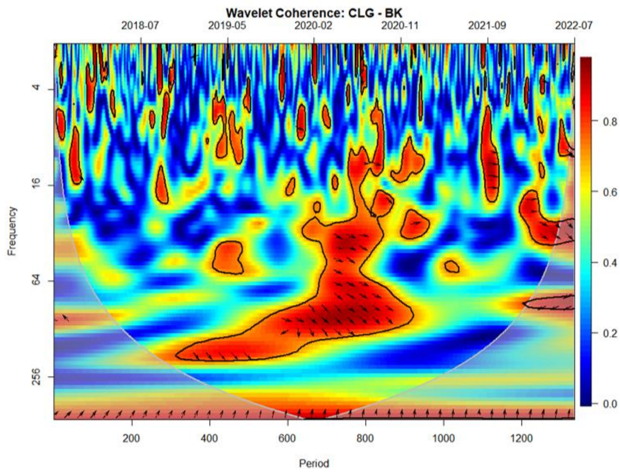


Figure 4. Correlation strength and lead-lag relationship between the CLG and Goldman Sachs (GS) in different frequency domains

Figure 4 provides an in-depth analysis of the dynamic correlation between the CLG and the Bank of New York Mellon (BK). In the short-run frequency domain (4-16 days), the correlation between CLG and BK exhibits significant intermittency and volatility. Several discrete high-correlation regions appear during the study period, most notably in the second half of 2018 and late 2020. The arrow directions within these high-correlation regions vary, showing complex mutual influence patterns between the two markets in the short term, reflecting investors' different interpretations and reactions to short-run market information.

The correlation pattern in the medium-term frequency domain (16-64 days) reveals stronger coherence. Particularly noteworthy is the emergence of a significant high-correlation region from the third to the fourth quarter of 2020. The arrows during this period mainly point to the right and slightly upward, indicating that the clean energy market leads the market movements of the Bank of New York Mellon to some extent. This phenomenon may be related to the rapid recovery of the clean energy sector and the advancement of global energy transition policies in the later stage of COVID-19.

In the long-term frequency domain (64-256 days), we observe the most significant correlation characteristics. A large-scale red high-correlation region forms from early 2020 and persists until the end of 2020. The arrow direction within this region is relatively consistent, pointing to the lower right, suggesting that the market movements of the Bank of New York Mellon slightly lead theclean energies in the long run. This phenomenon may reflect the first-mover advantage of traditional financial institutions in responding to systemic risks.

Entering 2021, market linkages undergo significant structural changes. In the short-run and medium-term frequency domains, the correlation strength generally weakens, but a significant high-correlation region emerges again in the third quarter of 2021. The strengthening of correlations during this period may be related to financial institutions' adjustments to clean energy investment strategies in the context of global economic recovery.

Data from the first half of 2022 show that the correlations between the two markets are mainly concentrated in the short-run and medium-term frequency domains and exhibit a more dispersed distribution. This change may reflect market participants adopting more cautious and differentiated investment strategies when facing the new economic environment (Wang *et al*.,2024).

Overall, the correlation between CLG and BK exhibits significant time-varying characteristics and scale dependence. This dynamic relationship not only reflects the complex interactions between traditional financial institutions and emerging energy markets but also reveals the profound impact of external events on market linkage mechanisms. The research findings further suggest that when constructing investment portfolios and conducting risk management, it is necessary to fully consider the time-varying characteristics and multi-scale properties of market correlations. At the same time, these findings also have important implications for understanding the role positioning of financial institutions in the clean energy transition process.

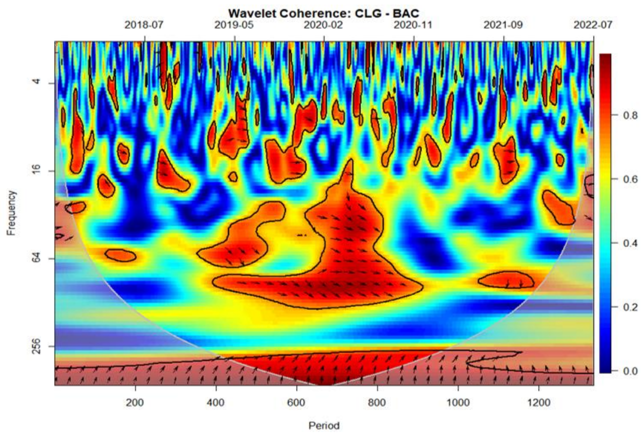


Figure 5. Dynamic correlation characteristics between the CLG and Bank of America (BAC)

Figure 5 explores the dynamic correlation characteristics between the CLG and Bank of America (BAC). In the short-run frequency domain (4-16 days), the correlation between CLG and BAC exhibits highly dispersed and frequently changing characteristics. Several independent high-correlation regions appear during the study period, most notably in mid-2019 and the fourth quarter of 2020. The arrow directions within these high-correlation regions vary, indicating a bidirectional flow of information between the two markets in the short term, reflecting investors' different response strategies to short-run market fluctuations.

The medium-term frequency domain (16-64 days) reveals a more coherent and stable correlation pattern. Particularly during the second to the third quarter of 2020, a significant high-correlation region is formed. The arrows during this period mainly point to the right, indicating that the movements of the two markets tend to be synchronous. This phenomenon may be related to the overall fluctuations of financial markets during COVID-19 and the advancement of clean energy policies.

In the long-term frequency domain (64-256 days), we observe the most representative correlation characteristics. A long-lasting and wide-ranging red high-correlation region forms from late 2019 and extends until the end of 2020. The arrows within this region are generally pointing to the right and slightly downward, indicating that the market movements of Bank of America slightly lead theclean energies in the long run, reflecting the potential information advantage of traditional financial institutions in responding to systemic risks.

The market interactions in 2021 exhibit new features. Correlations in all frequency domains show significant fluctuations, with a significant high-correlation region emerging in the medium-term frequency domain in the third quarter. This change may be related to financial institutions' adjustments to clean energy investment strategies during the economic recovery process in the post-COVID-19 era.

It is noteworthy that data from the first half of 2022 show that the correlations between the two markets are mainly concentrated in the short-run and medium-term frequency domains and exhibit a relatively scattered distribution pattern. This change may reflect market participants adopting more flexible and differentiated investment strategies when facing the new economic environment and policy changes.

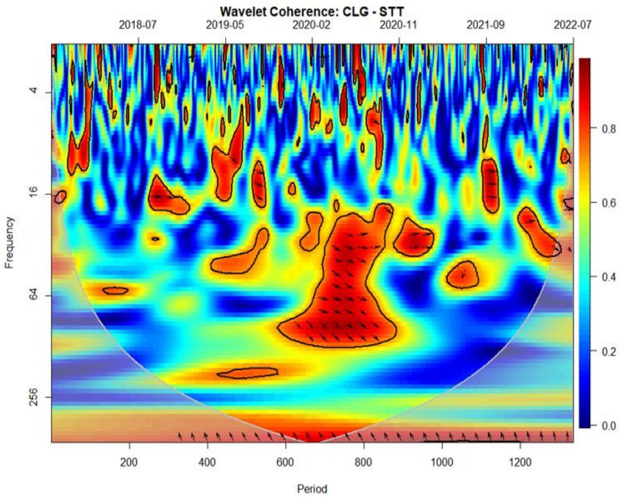


Figure 6. Dynamic correlation between the CLG and State Street Bank (STT)

Figure 6 examines the dynamic correlation between the CLG and State Street Corporation (STT). Through an in-depth analysis of time-frequency domain data, we reveal the unique interaction patterns and evolution characteristics of the two markets at different time scales.

The analysis in the short-run frequency domain (4-16 days) shows that the correlation between CLG and STT exhibits highly discrete and frequently fluctuating characteristics. Several independent high-correlation regions appear during the study period, particularly significant in the second half of 2018 and mid-2019. The arrow directions within these high-correlation regions are diverse, indicating complex mutual influence mechanisms between the two markets in the short term. This may reflect investors' differentiated interpretations and reactions to short-run market information.

The medium-term frequency domain (16-64 days) reveals relatively more stable correlation characteristics. Particularly in the third quarter of 2020, a significant high-correlation region is formed. The arrows within this region mainly point to the right and slightly downward, suggesting that the market movements of State Street Corporation slightly lead theclean energies during this period. This phenomenon may be related to the higher sensitivity of financial institutions to market risks during COVID-19.

The long-term frequency domain (64-256 days) exhibits the most significant correlation characteristics. A long-lasting red high-correlation region forms from early 2020 and extends to the end of 2020. The arrow direction within this region is relatively consistent, pointing to the right, indicating that the two markets maintain synchronous movements in the long run, reflecting the common impact of systemic risks on both markets.

Entering 2021, market linkages exhibit new changing characteristics. Correlations in all frequency domains show strong volatility, with a noticeable high-correlation region emerging in the medium-term frequency domain in the third quarter of 2021. This change may be related to financial institutions' adjustments to clean energy investment strategies during the global economic recovery process. Data from the first half of 2022 show that the correlations between the two markets are mainly distributed in the short-run and medium-term frequency domains and exhibit relatively dispersed characteristics. This changing trend may reflect market participants adopting more prudent and flexible investment strategies when facing the new economic environment and policy changes. The research results not only reveal the significant time-varying characteristics and scale dependence between State Street Corporation and the clean energy market but also highlight the profound impact of major external events on market linkage mechanisms.

Figure 7 explores the dynamic correlation characteristics between the CLG and Wells Fargo (WFC). In the analysis of the short-run frequency domain (4-16 days), the correlation between CLG and WFC exhibits significant intermittency and instability. Several scattered high-correlation regions appear during the study period, most notably in the third quarter of 2018 and mid-2019. The arrow directions within these regions vary, reflecting the complex bidirectional information transmission mechanisms between the two markets in the short term. This phenomenon may stem from investors' differentiated reactions to short-run market information.

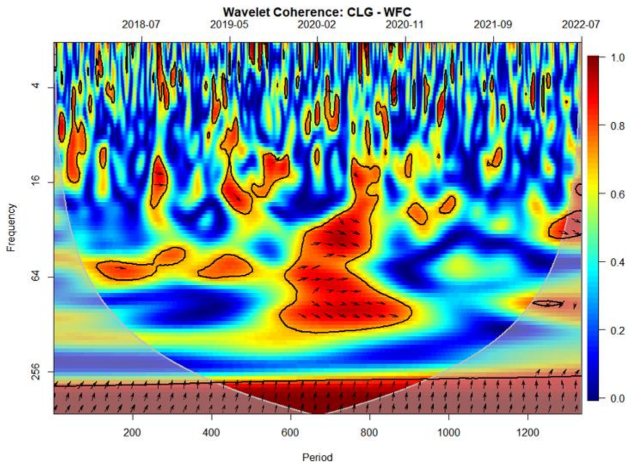


Figure 7. Dynamic correlation characteristics of the CLG and Wells Fargo Bank (WFC)

The medium-term frequency domain (16-64 days) reveals a more coherent correlation pattern. Notably, a significant high-correlation region forms in the third quarter of 2020, with arrows mainly pointing to the right, indicating that the movements of the two markets tend to be synchronous during this period. This synchronization may be related to the overall fluctuations of financial markets during COVID-19 and the advancement of clean energy policies.

The long-term frequency domain (64-256 days) exhibits the most significant correlation characteristics. A long-lasting red high-correlation region forms from early 2020 and extends until the end of 2020. The arrow direction within this region is relatively consistent, pointing to the right and slightly downward, indicating that the market movements of Wells Fargo slightly lead theclean energies in the long run, reflecting the potential information advantage of traditional financial institutions in responding to systemic risks.

Entering 2021, the interaction relationship between the two markets undergoes noticeable changes. Correlations in all frequency domains show large fluctuations, with a relatively weak correlation emerging in the medium-term frequency domain in the third quarter of 2021. This changing trend may be related to financial institutions' adjustments to clean energy investment strategies during the economic recovery process in the post-COVID-19 era.

Data from the first half of 2022 show that correlations are mainly concentrated in the short-run and medium-term frequency domains and exhibit relatively dispersed characteristics. This changing trend reflects market participants adopting more prudent and flexible investment strategies when facing the new economic environment and policy changes. The low correlations during this period may also be related to adjustments in Wells Fargo's own business strategies.

Figure 8 reveals complex correlation characteristics between the clean energies and the Morgan Stanley index. In the lower frequency range (2-4 days), the overall correlation is relatively weak from low to high quantiles, indicating weak linkage between the two markets in the short term. This may be due to the unique short-run fluctuation characteristics of the clean energy market, influenced by specific factors such as policy support and technological progress.

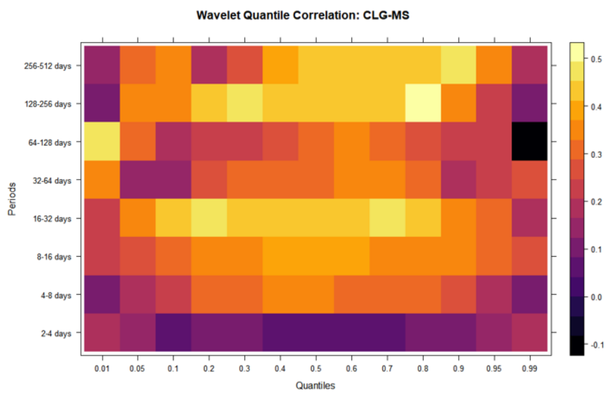


Figure 8. WQC correlation characteristics of the clean energies and the Morgan Stanley Index

In the medium frequency range (16-32 days), the overall correlation is relatively strong and positive from low to high quantiles, with correlation coefficients generally between 0.4-0.5. This medium-term positive correlation reflects the strong linkage effect between the clean energy market and the overall stock market on a monthly scale, possibly due to their common influence by systemic factors such as macroeconomic factors and market sentiment. This positive correlation is more significant in the 0.2-0.8 quantile range.

In the higher frequency ranges (128-256 days and 256-512 days), the correlation pattern exhibits distinct differentiation characteristics. Weaker correlations are present in the low quantile (0.01-0.2) and high quantile (0.8-0.99) regions, while relatively stable positive correlations are maintained in the medium quantile region. This differentiation of long-term correlations indicates that under extreme market conditions (corresponding to low and high quantiles), the clean energy market may exhibit different performance from the overall stock market, possibly related to factors such as the long-term development strategy of the clean energy industry, policy support strength, and technological innovation cycles (Zou *et al.*,2024).

In the 4-8 day and 8-16 day frequency ranges, the overall correlation is of medium strength, with relatively smooth variations between different quantiles. This indicates a stable linkage between the two markets on a short to medium-term time scale, possibly reflecting the similarity of trading behaviours and risk management strategies of market participants within this time range.

Figure 9 displays the quantile correlation characteristics between the clean energies and the JPMorgan Chase index. In the shortest 2-4 day frequency range, the two indices exhibit extremely weak correlations, almost approaching zero, indicating strong independence between the fluctuations of the clean energy market and the JPMorgan Chase index at the daily trading level. This characteristic may stem from the differences in market factors and investor behaviours affecting the two markets in the short term.

The short to medium-term frequency range (16-32 days) shows significant positive correlations, especially in the medium quantile range of 0.3-0.7, with correlation coefficients reaching around 0.4. This feature reflects the stable linkage between the clean energy market and the JPMorgan Chase index on a monthly time scale. This linkage may be due to the consistency of institutional investors' ass*et al*location strategies and risk management behaviours within this time range.

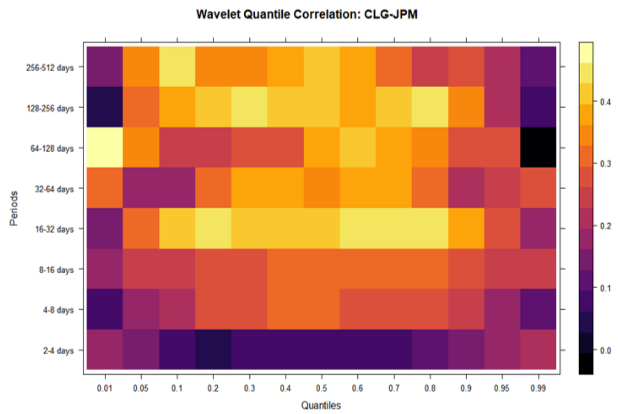


Figure 9. WQC correlation characteristics of the clean energies and the JP Morgan Index

In the longer-term 128-256 day and 256-512 day frequency ranges, the correlations exhibit distinct asymmetric characteristics. Relatively stable medium-strength positive correlations are maintained in the medium quantile region (0.3-0.7), while significantly weak or even negative correlations are present in the extreme quantile regions (0.01-0.1 and 0.9-0.99). This asymmetry suggests that under extreme market conditions, the clean energy market may exhibit different long-term performance trends from the JPMorgan Chase index, possibly related to the unique long-term development cycles of the clean energy industry and changes in financial institutions' risk preferences.

In the short to medium-term 4-8 day and 8-16 day frequency ranges, the overall correlation shows an increasing trend from low to high quantiles, forming a sharp contrast with the previously analysed Morgan Stanley index.

Figure 10 reveals the unique correlation patterns between the clean energies and the Goldman Sachs index. In the lowest 2-4 day frequency range, the two indices exhibit significant negative correlations, particularly around the 0.1 quantile, with correlation coefficients approaching -0.1. This short-run negative correlation suggests the possibility of hedging effects between the two markets in daily trading, which may be related to Goldman Sachs' special role as an investment bank in the clean energy market, possibly adopting different trading strategies in the short term.

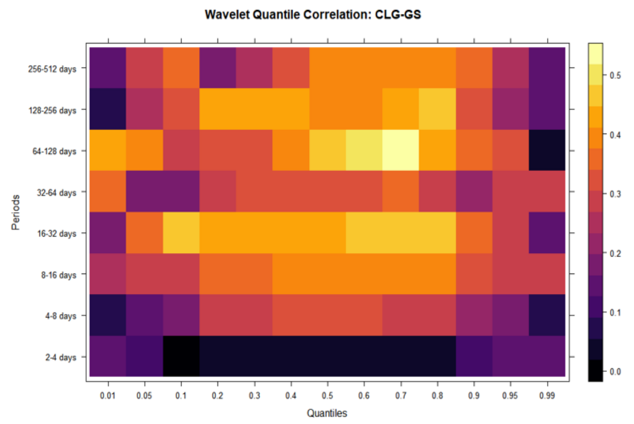


Figure 10. WQC correlation characteristics of the clean energies and the Goldman Sachs Index

In the 16-32 day frequency range, the correlation exhibits a distinct "plateau" feature, maintaining stable positive correlations in the 0.2-0.8 quantile range, with correlation coefficients between 0.4-0.5. This stable medium-term positive correlation indicates that Goldman Sachs' market activities have a solid connection with the clean energy market on a monthly scale, possibly reflecting Goldman Sachs' important role in clean energy project financing and market making.

The 64-128 day and 128-256 day frequency ranges display unique "block-like" correlation patterns, with high correlation value regions appearing in the 0.5-0.7 quantile range, and correlation coefficients exceeding 0.5. This concentrated area of strong correlations on a quarterly scale reflects the deep linkage between Goldman Sachs and the clean energy market in medium to long-term investment cycles, possibly related to its strategic investments and asset management business in the clean energy field.

The correlation in the highest 256-512 day frequency range exhibits a distinct "U-shaped" distribution feature, maintaining strong positive correlations in the medium quantile region, while rapidly attenuating in the extreme quantile regions. This non-linear feature of long-term correlations suggests that under extreme market conditions, the relationship between Goldman Sachs and the clean energy market may undergo qualitative changes, possibly stemming from special market environments during financial crises or periods of structural market reforms.

In the short-run 4-8 day and 8-16 day frequency ranges, the overall correlation exhibits a gradual feature from weak to strong, forming a sharp contrast with the correlation patterns of other financial institution indices, possibly reflecting Goldman Sachs' unique trading strategies and risk management approaches in the clean energy market. This differentiated correlation structure provides a new perspective for understanding the roles and influences of different financial institutions in the clean energy market.

Figure 11 reveals the complex correlation structure between theclean energies and the BK index. In the shortest 2-4 day frequency range, the correlation exhibits significant fluctuation characteristics, with a notable positive correlation peak appearing at the 0.01 quantile, while maintaining a lower level in the 0.2-0.7 quantile range. This unique short-run correlation structure may reflect the existence of a special interaction mechanism between the BK index and the clean energy market in intraday trading.

Figure 11. WQC correlation characteristics of clean energies and BK index

The most significant feature appears in the 16-32 day frequency range, with correlation coefficients reaching a maximum value of around 0.4 in the 0.3-0.7 quantile range and exhibiting a stable "band-like" distribution. This concentration of medium-term correlations indicates the existence of a stable linkage between the BK index and the clean energy market on a monthly scale, possibly due to the similar response patterns of the two markets to common macroeconomic factors and market sentiment within this time range.

In the 64-128 day and 128-256 day frequency ranges, the correlation exhibits a distinct "mosaic" structure, forming multiple alternating blocks of strong and weak correlations in different quantile regions. This unique correlation distribution pattern indicates that on a quarterly and semi-annual scale, the relationship between the BK index and the clean energy market is influenced by multiple factors, possibly including seasonal fluctuations, financial reporting cycles, and changes in industry policies.

The correlation in the highest 256-512 day frequency range displays a "gradient" change characteristic, gradually weakening from low to high quantiles. This gradual feature of long-term correlations suggests the possibility of a structural transformation relationship between the BK index and the clean energy market over long-term investment cycles, forming a sharp contrast with the "U-shaped" or "block-like" distributions exhibited by other financial institution indices.

In the short to medium-term 4-8 day and 8-16 day frequency ranges, the overall correlation exhibits a relatively flat distribution, but local correlation enhancements appear in specific quantile regions. This phenomenon may reflect the existence of certain specific trading patterns or risk transmission mechanisms between the BK index and the clean energy market on this time scale. This unique correlation characteristic provides a new research perspective for understanding the interaction relationship between financial institutions and emerging energy markets.

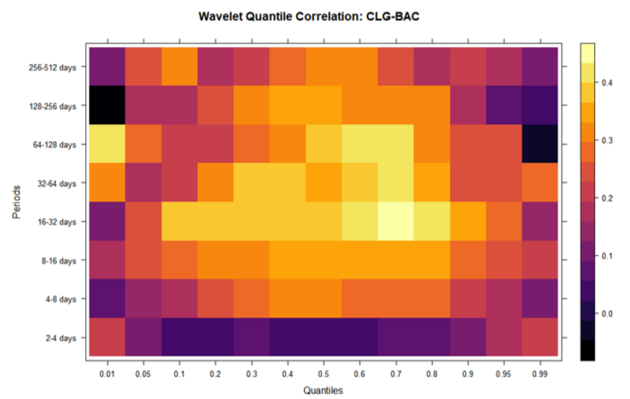


Figure 12. WQC correlation characteristics of the clean energies and the US Bank Index

Figure 12's WQC plot reveals the dynamic correlation characteristics between the clean energies and the Bank of America index. In the ultra-short-run 2-4 day frequency range, the two indices exhibit a significant non-linear relationship, with a positive correlation peak appearing at the extremely low quantile (0.01), while maintaining a level close to zero in the 0.1-0.8 quantile range. This unique correlation structure reflects the existence of a certain asymmetric short-run risk transmission mechanism between Bank of America and the clean energy market in daily trading.

The medium-term 16-32 day frequency range displays a striking "butterfly-shaped" correlation distribution, forming a stable high-correlation region in the medium quantile range of 0.3-0.7, with correlation coefficients maintained at around 0.4. This characteristic correlation structure suggests the existence of stable synergistic effects between Bank of America and the clean energy market on a monthly scale, possibly related to its systemic participation in clean energy project financing and market making.

In the 64-128 day frequency range, the correlation exhibits a unique "mosaic" distribution pattern, forming multiple discrete correlation concentration areas in different quantile regions. This uneven correlation distribution on a quarterly scale may reflect the cyclical adjustments in Bank of America's investment strategies in the clean energy field as market environments change, which is consistent with its prudent investment attitude as a traditional financial institution in emerging industries.

The correlation in the longest 256-512 day frequency range displays a distinct "step-like" attenuation feature, gradually decreasing from medium quantiles towards both ends. This orderly attenuation pattern of long-term correlations suggests the possibility of a certain systemic risk management mechanism between Bank of America and the clean energy market in long-term investment cycles, with this mechanism becoming more evident under extreme market conditions.

In the short to medium-term 8-16 day and 32-64 day frequency ranges, the correlation distribution exhibits a relatively smooth gradual change feature, but local correlation enhancement points appear at specific quantiles. This phenomenon may reflect the adoption of specific trading strategies or risk hedging schemes by Bank of America on these time scales.

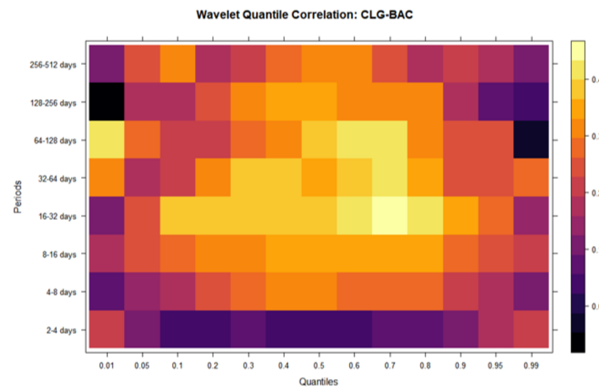


Figure 13. WQC correlation characteristics of clean energies and State Street Bank Index

Figure 13 showcases the complex correlation characteristics between the clean energies and the State Street Corporation index. In the shortest 2-4 day frequency range, the correlation exhibits significant volatility, with positive correlations appearing at the 0.01 quantile, while presenting near-zero or even slight negative correlations in the 0.1-0.8 quantile range. This unstable characteristic of short-run correlations may reflect the existence of a certain unique short-run risk interaction mechanism between State Street Corporation, as one of the world's largest custody banks, and the clean energy market in its daily trading activities.

The medium-term 16-32 day frequency range displays a significant "bright band" feature, forming a high-correlation region in the 0.3-0.7 quantile range, with correlation coefficients reaching a maximum of around 0.5. This band-like distribution of the correlation structure indicates the existence of stable linkage effects between State Street Corporation and the clean energy market on a monthly scale, possibly stemming from its important intermediary role as an institutional investor service provider in clean energy investments.

In the 64-128 day and 128-256 day frequency ranges, the correlation exhibits a complex "chessboard" pattern, forming alternating blocks of high and low correlations in different quantile regions. This irregular correlation distribution on a quarterly and semi-annual scale may reflect the dynamic adjustments in State Street Corporation's asset servicing strategies in the clean energy field as market cycles and client demands change.

In the longest 256-512 day frequency range, the correlation displays a distinct "wave" shape, maintaining relatively stable positive correlations in the medium quantile region, while exhibiting significant attenuation in the extreme quantile regions. This fluctuating characteristic of long-term correlations suggests the possibility of certain cyclical structural changes between State Street Corporation and the clean energy market in long-term investment cycles, which is highly related to the characteristics of its global asset management and custody business.

In the short to medium-term 4-8 day and 32-64 day frequency ranges, the correlation distribution exhibits a gradual change feature, but local correlation jumps appear at specific quantiles. This phenomenon may be related to State Street Corporation's specific business activities on these time scales, such as ETF management and asset rebalancing operations. These unique correlation patterns provide a new analytical perspective for understanding the interaction relationship between global custody banks and emerging energy markets.

Figure 14 provides the time-frequency correlation characteristics between theclean energies and the Wells Fargo index. In the shortest 2-4 day frequency range, the correlation exhibits a unique "breakage" feature, with a strong positive correlation appearing at the extremely low quantile (0.01), while presenting a near-zero correlation in the 0.2-0.8 quantile range. This significant short-run correlation breakage phenomenon may reflect Wells Fargo's adoption of risk management strategies that are relatively independent of the clean energy market in daily trading.

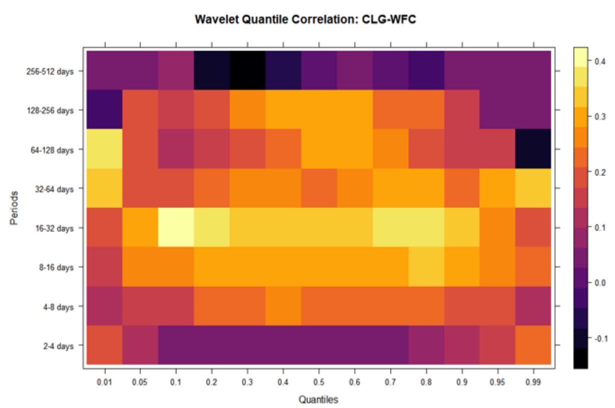


Figure 14. WQC correlation characteristics of the clean energies and the Wells Fargo Index

The medium-term 16-32 day frequency range displays the most significant "stripe-like" correlation structure, forming a continuous high-correlation region from the 0.1 to 0.8 quantile range, with correlation coefficients stably maintained at around 0.4. This stable medium-term positive correlation suggests that Wells Fargo maintains stable business connections with the clean energy market within the monthly investment cycle, possibly related to its strategic layout in clean energy project financing and sustainable development investments.

In the 128-256 day frequency range, the correlation exhibits a distinct "island-like" distribution feature, forming a high-correlation concentration area in the 0.4-0.7 quantile range, while surrounding regions present lower correlations. This unique quarterly-scale correlation distribution may reflect Wells Fargo's seasonal business adjustments and risk preference changes in the clean energy field, aligning with its strategy of transitioning from a traditional commercial bank to sustainable finance.

The longest 256-512 day frequency range exhibits a significant negative correlation region, particularly in the 0.3-0.4 quantile range, with correlation coefficients dropping below -0.1. The emergence of this long-term negative correlation suggests the possibility of a certain hedging relationship between Wells Fargo and the clean energy market in long-term investment cycles, a phenomenon that is relatively rare in other financial institution indices.

In the short to medium-term 8-16 day and 32-64 day frequency ranges, the correlation exhibits a smooth gradual change feature, but significant positive correlation peaks appear in the low quantile region. This phenomenon may reflect Wells Fargo's adoption of specific trading strategies or ass*et al*location schemes on these time scales. These unique correlation characteristics provide a new perspective for understanding the complex relationship between traditional commercial banks and emerging energy markets.

4. Conclusion and implications

In the context of global climate change and energy transition, the development of the clean energy industry is increasingly interconnected with the stability of the financial system. Existing literature has rarely focused on the dynamic correlation characteristics between the clean energy market and systemically important banks, especially the interaction mechanisms at different time scales and under different market conditions. This study uses methods such as wavelet analysis, quantile correlation, and Granger causality tests to systematically examine, for the first time, the correlation characteristics between the U.S.clean energies and the stock returns of seven systemically important banks from the perspective of time-frequency domain and quantiles, filling the gap in related research.

The study has found four main innovative conclusions. First, the clean energies has significant predictive power for the stock returns of systemically important banks, especially for institutions with asset management and investment banking as their main businesses (such as State Street Corporation and Morgan Stanley), with F-statistics reaching 7.3147 and 7.1673, respectively. Second, the linkage between the two markets exhibits significant scale-dependent characteristics, gradually transitioning from intermittent correlations in the short term to persistent strong correlations in the long term. Third, market linkages have obvious non-linearity and asymmetry, maintaining stable positive correlations in the medium quantile range (0.3-0.7), while showing significant attenuation or negative correlations in the extreme quantile regions. Fourth, after 2021, market linkages have undergone structural changes, reflecting the adjustment of financial institutions' investment strategies in the post-COVID-19 era.

These findings have important policy implications for different stakeholders:

For financial regulatory authorities, it is necessary to construct a multi-dimensional risk monitoring system. It is recommended to incorporate clean energy market fluctuations into the systemic risk assessment framework, paying particular attention to the risk transmission mechanisms at different time scales. For example, a stress testing scheme that includes clean energy exposure can be established to assess potential risks under extreme market conditions.

For commercial banks, credit structures and risk management strategies should be optimised. It is recommended to formulate differentiated clean energy credit policies based on the time-frequency characteristics revealed in this study. For instance, long-term project loans can be combined with short-run credit support, and risk limits can be dynamically adjusted according to market conditions.

For investors, this study provides new ideas for portfolio optimisation. It is recommended to flexibly adjust the allocation ratio of clean energy and financial stocks under different market environments. For example, in extreme market conditions, the allocation of clean energy can be appropriately increased to achieve risk hedging, while in normal market environments, stable positive correlations can be used to obtain synergistic returns.

The practical application value of this study is mainly reflected in three aspects. First, regulatory authorities can draw on the analytical framework of this paper to improve the early warning mechanism for systemic risks. Second, banks can optimise the risk pricing model of clean energy-related businesses based on the research findings. Finally, investment institutions can incorporate the time-frequency characteristics and non-linear characteristics of this study into the design of quantitative investment strategies.

Of course, this study also has certain limitations. First, the sample period is relatively short and may not fully capture the long-term evolutionary characteristics. Second, the study has not been able to delve into the impact mechanism of policy changes on market linkages. These issues are worth further exploration in future research.

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