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Article

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The Impact of Digital Finance on Clean Energy and Green Bonds through the Dynamics of Spillover

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ABSTRACT

The primary objective of this research is to employ a novel time-varying causality test to establish the causal link between green technology, clean energy, digital finance, and environmental responsibility. The research study has used the time-varying Vector autoregression (VAR) method to analyze the relationship between digital finance on clean energy and green bonds through dynamic spillover in China from 2011 to 2019. In addition, for robustness, a spillover dynamic connectedness model is implemented. The empirical results show that the spillover shocks analysis comes from the clean energy to digital finance index (30.544%), followed by propagation from clean energy to green economic index (28.234%). Depending on economic events, the total connectedness across assets changes over time. Long-term Environmental costs are dramatically reduced by 0.68% with every 1% increase in clean energy consumption. However, the entire period from clean energy to digital finance is marked by heightened volatility and causal relevance. The study found that after the local economy and environmental governance, the institutional environment has the second-largest impact on the market expansion for green bonds. The findings add to our understanding of the risk profile of clean energy stocks and emphasize the need for stable, predictable laws to increase the marketability of pure energy stocks.

Keywords: Digital Finance, Clean Energy, Green Technology, Green Bonds, TVP-VAR Technique
JEL Classifications: C36, E44, E39, F14

1. INTRODUCTION

Climate change is an undeniable fact (Ahmad et al., 2019). World rising temperature has become a severe threat to global climate hazards and greenhouse gas emissions to the agriculture sector (Beddu et al., 2022; Ashraf et al., 2022; Blanco et al., 2021). Lin and Zhu (2019) claimed that climate change will deplete nearly 10% of global economic value by 2050. Therefore, the Paris Agreement mainly concerns climate change mitigation and adaptation techniques. Clean energy, green bond issuance, and carbon pricing are just a few techniques that could reduce carbon emissions (Hosseini et al., 2013; Abid, 2017; Ahmad et al., 2022). Renewable energy projects to reduce carbon emissions and green finance are essential by 2050 (Chen and Lei, 2018). Green bonds are a crucial source of funding and a diverse investment option for investors and enterprises that care about the environment (Liu and Song, 2020). Green bonds have the benefits of having enormous development potential by investing in clean and renewable energy and the environment (Chiesa and Barua, 2019; Ren et al., 2022).

Economic growth and financial development are closely linked with greenhouse gas emissions, and rapid urbanization and a large population harm the environment and are significant causes of greenhouse gas emissions (Nieuwenhuijsen, 2021). However, more research needs to be done on how clean energy regulations affect business productivity. It is noteworthy that. They have created a wide field of study to understand the elements that affect an economy's long-term growth and determine whether there is evidence of global convergence in GDP per person (Mukanjari and Sterner, 2020; Cetin et al., 2018). World leaders should pay more intention to global issues such as climate change and environmental standards to avoid environmental degradation (Ali et al., 2022). According to Mohsin et al. (2019), green bonds have a low and negative correlation with stocks and commodities over time. The rapid rise in the worldwide clean energy sector is being threatened by digital finance (Cao et al., 2021).

This paper offers empirical support for the conditions that propelled the market for green bonds in China to proliferate. China's green bond market is unique from the global green bond market in that it was created in response to a bottom-up set of regulations, or a set of "hard laws," which ensure that the green bond market will proliferate. This study examined the effects of environmental governance and local government policy assistance on the growth of the green bond market. According to Wang et al. (2020), policy backing and a green development plan are crucial to the growth of China's green bond market. The significance of the study is to provide empirical evidence to demonstrate the market's rapid growth in China and to study the factors that drive the green financial market.

2. LITERATURE REVIEW

2.1. Clean Energy

Globalization is the biggest challenge in achieving the clean energy resources target, and supply chain management (SCM) concern for clean energy is increasing worldwide. Therefore, there is a dire need to identify and measure the barriers to sustainable clean energy technology. Manufacturing organizations increasingly focus on implementing numerous techniques to increase pure energy efficiency (Borowski, 2021). Natural disasters or human-made problems may cause risk, which can have significant implications for businesses regarding financial and organizational difficulties, resulting in business interruptions (Lin et al., 2022). Moreover, numerous market trends, such as subcontracting, reducing the supply base, and shortened product life cycles, have expanded the industry's clean energy threat experience (Cao et al., 2021; Acheampong, 2018).

Clean energy was explored by Akrofi and Antwi (2020) during the Covid-19 pandemic, examined the African government's economic stimulus strategy for the clean energy industry, and committed to advancing the nation's switch to clean energy. Using Malaysia as an example, Rahman et al. (2021) demonstrated how digital finance might have a tremendous environmental impact by increasing clean energy production. Li et al. (2012) studied China to show worries regarding the Green New Deal. Apergis and Payne (2009) used the fuzzy multiple-criteria decision-making (MCDM) technique based on TODIM-D, present a framework for prioritizing the activities connected to zero-carbon technologies looked into how the issuing of corporate green bonds may affect the issuer's financial performance; they discovered that the market would likely respond negatively, just like it would with conventional or convertible bonds. Çevik et al. (2019) used wavelet analysis to assess the multistage level in the long run and show a strong correlation between green bonds with clean energy.

2.2. Green Bond

Chinese green bonds market has been expanding, and about 39.0% of the total worldwide green government borrowing in 2016 came from China (Hu, 2016). The term "From Zero to Hero" is used by confident foreign investors (Fuhrman et al., 2019). Data from the 27 industrialized countries that issued green bonds shows that fast and high rates of economic expansion also improve environmental quality in the long run (Saboori et al., 2022). Owen et al. (2018) evaluated the characteristics of the industrial structure and discussed the potential contribution of green finance to the industrial transformation. The Paris agreement is the commitment of 195 countries to reduce global warming by investing in green bonds; therefore, many countries have launched green bonds in response to the Paris agreement (Cortellini and Panetta, 2021; Adams and Klobodu, 2018). The Islamic nations also issued green bonds through Malaysia's "green Sukuk" bonds in 2017 (Tang and Zhang, 2020). Green bond issuance spreads from Europe to many emerging countries, particularly in China, as shown in Figure 1. Although the green bond market has doubled its size, yet founds a small portion of the overall bond market, accounting for around 3% of total global bond issuances in 2019 (Syzdykov and Lacombe, 2020).

3. DATA AND METHODS

The China sample for this analysis was the A-share clean energy market. Data from 2001 to 2019 were used in this analysis to infer the China region. The study identified countries issuing green bonds using the World Bank database (2018). In order to prepare the data for empirical analysis, errors were removed.

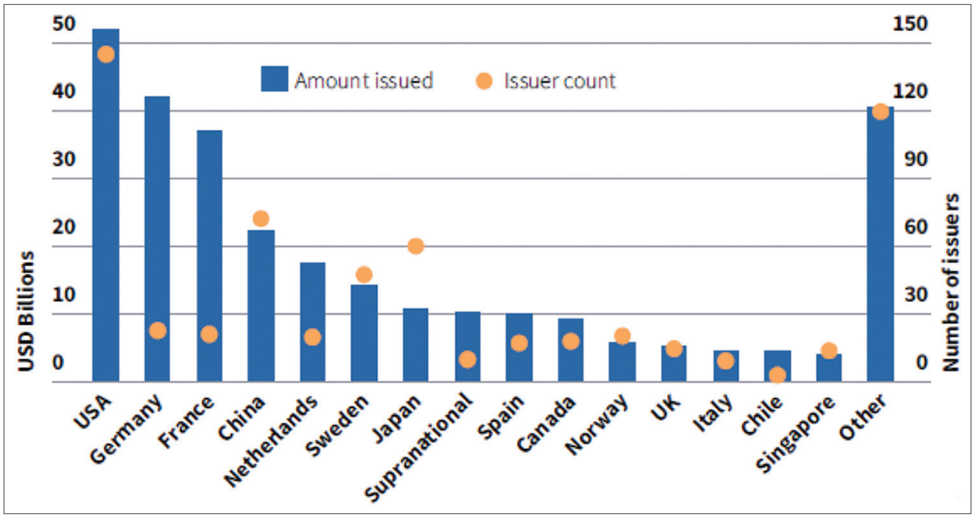
1. Green bond prices: Green bonds are measured in terms of their prices, which are the pricing units
2. Green growth index (GGI): By creating a solid link between clean energy, the environment, and the economy, the green growth index aids in measuring green growth
3. Green economy index (G.E.): This metric strikes a balance between effectiveness
4. Digital finance indicator (DFI): This covers market size, Digital finance price demand sensitivity
5. Digital finance investment cost, Digital finance retention rate.

All control variables are researched over the same period as the clean energy (C.E.), from 2001 to 2019.

3.1. Descriptive Statistics

Data from the daily returns are summarized in Table 1. The daily mean for all series is positive when we look at the mean returns. The mean green bond prices (4.290), the green growth index (9.728), the green economy index, the digital finance indicator, and digital finance investment are 7.578, 6.891, and

Figure 1: Green bond amount issued by the countries (2020)



(Source: Harrison and Muething, 2021, p.7)

Table 1: Results of descriptive statistical summary

Variable	Obs	Mean	SD	Minimum	GGI	GE	CE	GB
DFI	700	6.891	1.521	−6.330	6.340	6.870	8.450	8.590
CE	700	7.578	2.594	−0.660	5.740	6.920	8.340	12.23
GGI	700	9.728	4.716	1.330	4.670	12.15	13.52	16.19
GDP	700	9.51	0.622	6.198	11.30	8.44	10.32	13.62
ST	700	2.322	0.988	0.244	0.655	0.867	1.044	3.766
IS	700	0.867	0.174	0.689	0.769	0.645	0.612	0.978
GP	700	5.244	4.233	0	5	7	9	16
GB	700	4.290	3.456	0	3	6	7	10
EL	700	9.67	1.890	3.967	7.567	8.55	14.72	2.44
INDS	700	1.977	1.256	0.012	0.766	1.980	2.633	7

SD: Standard deviation, GGI: Green growth index, CE: Clean energy, DFI: Digital finance indicator, GE: Green economy index

1.977, respectively. Green bonds consequently have the lowest mean estimate and standard deviation among all the series used. However, digital finance energy, green bond energy, and clean energy have little to do with carbon dioxide and green bonds. Furthermore, digital finance and clean energy have the most vital relationships, followed by green bond (G.B.) and clean energy (C.E.). These numbers support our decision to use a TVP-VAR technique with time-varying variance-covariance to model the interaction between those variables.

3.2. Methods

3.2.1. Vector auto regression (VAR) methods

This method is selected based on the Bayesian information criterion (BIC), which can be mathematically expressed as

$$y_t = B_t Y_{t-1} + \varepsilon_t \varepsilon_t \sim N\left(0, \sum\nolimits_t\right) \quad (1)$$

$$Vec\left(B_t\right) = Vec\left(B_{t-1}\right) + \upsilon_t \upsilon_t \sim N\left(0, \mathbb{S}_t\right) \quad (2)$$

y_t,y_{t-1} and ε_t are $K \times 1$ dimensional vectors, and B_t and $\sum_t$ are $K \times K$ dimensional matrices, respectively. STIs a $K2 \times K2$ dimensional matrix, whereas $vec\ (B_t)$ are $K^2 \times 1$ dimensional vectors.

$y_t = \sum_{h=0}^{\infty} A_{h,t}\varepsilon_{t-}$ is used to VAR to TVP representation: where $A_0 = I_K$.

The *H*–step in front of The GFEVD model simulates the effect of a shock in series *j* on series. It is expressed in equation (3)

$$\varphi_{ij,t}^{gen}\left(H\right) = \frac{\sum_{h=0}^{H-1}\left(e_i' A_{ht} \sum_t e_j\right)^2}{\left(e_i' \sum_i e_j\right)^{GB} \sum_{h=0}^{H-1}\left(e_i' A_{ht} \sum_t A_{ht}' e_j\right)} \quad (3)$$

$$\text{gSOT}_{\text{ij,t}} = \frac{\varphi_{ij,t}^{gen}\left(H\right)}{\sum_{k=1}^{K}\varphi_{ij,t}^{gen}\left(H\right)} \quad (4)$$

Where e_i is a $K \times 1$ dimensional zero vector at its *i* th position with unity. [42,43] Suggested $\varphi_{ij,t}^{gen}\left(H\right)$ normalizing the unsealed G.F. $\left(\sum_{k=1}^{K}\zeta_{ij,t}^{gen}\left(H\right) \neq 1\right)$, by dividing $\varphi_{ij,t}^{gen}\left(H\right)$ by the row sums to create the scaled G.F., $gSOT_{ij,t}$

The following formulas can be used to calculate these connectivity measures:

$$S_{i\to\bullet,t}^{gen,to} = \sum_{j=1,i\neq j}^{k}\text{gSOT}_{\text{ji},t} \quad (5)$$

$$S_{i\leftarrow\bullet,t}^{gen,from} = \sum_{j=1,i\neq j}^{k}\text{gSOT}_{\text{ij},t} \quad (6)$$

$$S_{i,t}^{gen,net} = S_{i\to\bullet,t}^{gen,to} - S_{i\leftarrow\bullet,t}^{gen,from} \quad (7)$$

If $S_{(i,t)}^{(gen,net)} > 0$ $\left(S_{i,t}^{gen,net} < 0\right)$, it is impacted by (influenced by) them and is thus a net shock transmitter with series I and j as shown by the net pairwise directional connectedness.

$$S_{ij,t}^{gen,net} = \text{gSOT}_{\text{ji},t} - \text{gSOT}_{\text{ij},t} \quad (8)$$

If $S_{ij,t}^{gen,net} > 0$ $\left(S_{ij,t}^{gen,net} < 0\right)$, series j, then series i influences

We must slightly alter the TCI to produce a TCI that is within $\left[0, \frac{K-1}{K}\right]$:

$$\text{gSOT}_{\text{t}} = \frac{1}{K-1}\sum\nolimits_{i=1}^{K} S_{i\leftarrow\blacklozenge,t}^{gen,from} = \frac{1}{K-1}\sum\nolimits_{i=1}^{K} S_{i\to\blacklozenge,t}^{gen,} \; too \quad (9)$$

Equation 9 allows traders to spread out their risk and trade on both the primary and secondary markets, giving them more options to make money and manage their finances. The green bonds market can grow in size and quality as the economy and development move toward more environmentally friendly. China is anticipated to have a substantial impact on increasing market efficiency. As an alternative, these bonds might contribute to the creation and maintenance of climate-friendly initiatives and a green energy economy.

$$\text{DF}_{\text{ij,t}}2 = \left(\frac{\text{gSOT}_{\text{ij},t} + \text{gSOT}_{\text{ji},t}}{\text{gSOT}_{\text{ii},t} + \text{gSOT}_{\text{ij},t} + \text{gSOT}_{\text{ji},t} + \text{gSOT}_{\text{jj},t}}\right)$$
$$,0 \le \text{CE}_{\text{ij,t}} \le 1. \quad (10)$$

Explain equation.

3.2.2. Models for portfolio back-tsting

Market players are eager to buy both stocks on the G.B. and C.E. marketplaces. This research study employed a consideration to acquire new insights into the relevance and employ a variety of estimating methodologies in portfolio creation, including traditional approaches and some recently developed connectedness-oriented portfolios. Our portfolio analysis is based on a variety of assumptions.

3.2.3. Green bond and the ratio of unilateral hedges

The dynamic hedge ratio proposed by Kroner and Sultan (1993) is as follows:

$$\beta_{ij,t} = \sum\nolimits_{\text{ij,t}} / \sum\nolimits_{\text{jj,t}}, \quad (11)$$

$$w_{\text{ij,t}} = \frac{\sum_{\text{ii,t}} - \sum_{\text{ij,t}}}{\sum_{\text{jj,t}} - 2\sum_{\text{ij,t}} + \sum_{\text{jj,t}}}, \quad (12)$$

$$w_{\text{ij,t}} = \begin{cases} 0, & if w_{\text{ij,t}} < 0 \\ w_{\text{ij,t}} if\ 0 \le w_{\text{ij,t}} \le 1 & \\ 1, & if w_{\text{ij,t}} > 1 \end{cases} \quad (13)$$

Is the weight of series I in a $1 portfolio split evenly across series I and j at time w (ij,t)? As a result, in the portfolio above, $1 - w_{ij,t}$ is the weight of series j at time t equals.

3.2.4. Minimum variance

The minimum variance (MV) technique, as documented by (Markowitz and Markowitz, 1959), is a regularly used strategy in portfolio analysis that aims to generate the portfolio with the least volatility based on many assets. The following formula is used to calculate portfolio weights:

$$w_{\sum_t} = \frac{\sum_t^{-1} I}{I \sum_t^{-1} I} \quad (14)$$

Where $w_{\sum t}$ indicates the $K \times 1$ dimensional Vector, I the K-dimensional vector variance-covariance matrix in period t.

3.2.5. Minimum correlation

Minimum correlation portfolios method is similar to MVP, but calculated by minimizing conditional correlations. As an example, consider the following:

$$R_{\mathbf{t}} = diag\left(\sum\nolimits_{\mathbf{t}}\right)^{-0.5} H_{\mathbf{t}} diag\left(\sum\nolimits_{\mathbf{t}}\right)^{-0.5} \quad (15)$$

$$w_{R_t} = \frac{R_t^{-1} I}{I R_t^{-1} I} \quad (16)$$

3.3. A Minimum of connectivity

After constructing the MV and MC portfolio approaches, research developed MCoP using pairwise connectedness indices instead of correlations or variances. The reduction of bilateral interconnectivity provides a portfolio technique that is less susceptible to network shocks. As a result, assets that do not affect or are influenced by others are given a larger weighting in the created portfolio. It can be represented as follows:

$$w_{C_t} = \frac{PCI_t^{-1} I}{I PCI_t^{-1} I} \quad (17)$$

The ratio is calculated as follows:

$$\text{SR} = \frac{\overline{r_p}}{\sqrt{\text{var}\left(r_p\right)}} \quad (18)$$

$$\text{HE}_i = 1 - \frac{\text{var}\left(r_p\right)}{\text{var}\left(r_i\right)} \quad (19)$$

Where var (r_p) represents portfolio variance, and $Varr_i$ represents asset i's variance. The HE_i index represents the percent reduction in the variance of unhedged asset position. A high (low) HE scores indicates a significant risk reduction.

4. EMPIRICAL RESULTS AND DISCUSSION

4.1. Vector Autoregression Model Structural Equation Models

Structural equation model was used using AMOS software to examine and test maximum likelihood estimation. It is revised following the results to get the best model and path coefficient. These findings suggest that green bond issuance may improve average firm performance; the overall effect, measured by the coefficient, is 1.65%. In terms of businesses, the issue of green bonds can be considered a green sign in light of the increasingly rigorous environmental requirements. The Structural equation model's indices is shown in Table 2 where C.E. is 2.524, GB1 is 0.997, and DFI is 6.659. These values match the criteria and demonstrate that the revised model has more incredible goodness of fit. The associated paths for hypotheses H1 through H5 are noted, and Table 2 lists the various path coefficients and significance levels. The influence mechanism coefficient supports all variable stationary processes with I (0) at the 1% level based on ADF test results.

4.2. Results of Connectedness Analysis

The geographical impact on cities and neighborhoods based on the spatial autoregressive model is considered to investigate further how green financing affects energy efficiency in Table 3. The amplitude of return shocks conveyed across variables varies significantly. Green bonds, followed by carbon price index returns, amount (to 2.246%.) throughout the complete sample of variables studied (5.724%). The most considerable spillovers shock analysis comes from the clean energy to digital finance index (30.544%), followed by propagation from clean energy to green economic index (30.544%). It is argued that green finance has a higher trading volume than conventional financing, green financing bonds offer lower risk pricing and greater liquidity. There have been a lot of green bonds issued by the Chinese banking industry, yet it is debatable whether the "cash-related strategy" motivates this development. The two steps of the green bond (G.B.) calculations are displayed explicitly in Table 3. Green bond issuance boosts the number of green bonds by 2.290%, while green patents encourage business growth by 1.230%. Green patents could convert novel technology supported by green bond investments into genuine commercial value as a result of green innovation efforts.

Chinese state green funding policy should be improved by encouraging inter-provincial cooperation and involvement in green bond returns (2.766%), followed by digital finance index 2.467%, and green bond (0.872% in the case of clean energy markets returns 2.290%. The corporation is anticipated to make some headway in addressing issues with environmental externality after issuing green bonds. The coefficient in column (5) is specifically discovered to be non-significant in the first phase, proving that green bonds have no discernible influence on enhancing the reputation for responsible. However, column (6) coefficient)'s is 2.446%, demonstrating that green bonds benefit the environment's reputation. The idea that it will be more challenging for older corporations to adapt their business model when coping with developing environmental challenges helps explain this outcome.

4.3. Results of ADF Unit Root Test

The connection between green technology, clean energy, and environmental responsibility is causative. With the help of the suggested recursive developing approaches, it is possible to pinpoint specific causation and instability in the link between clean energy and green technology, money, and environmental responsibility. We thus loosen the premise that there is a continuous causal relationship between clean energy and these variables throughout the sample period. By investigating the changing causation between clean energy and other economic, environmental, and financial factors, we contribute to the literature

Table 2: Results of influence mechanism coefficient and significance level

Panel A				
Factors		**Coefficient**		**CR**
DFI		0.567		6.659
CE		0.578		2.524
GGI		0.745		11.858
GDP		−0.140		−1.048
ST		0.030		0.243
IS		−0.150		0.000
GP		0.260		4.890
GB		−0.075		0.997
Panel B				
Standard effect	**Institutional environment**	**Local economy**	**Government support**	**Environment governance**
Total standard effect	0.089	0.322	−0.039	0.208
Direct effect	−0.121	0.190	−0.039	0.208
Indirect effect	0.230	0.009	0.000	0.000

DFI: Digital finance indicator, CE: Clean energy, GGI: Green growth index

Table 3: Results of green bound and economic recovery

Green variable	DFI	CE	GGI	GDP	ST	From others
DFI	92.271 (92.364)	1.230 (2.171)	2.214 (2.290)	2.623 (2.665)	0.872 (0.731)	7.731 (7.746)
CE	2.625 (1.512)	58.850 (59.289)	11.398 (10.699)	27.619 (28.134)	0.528 (0.685)	40.160 (40.821)
GGI	1.422 (1.341)	12.574 (12.744)	62.971 (62.119)	24.689 (24.520)	0.463 (0.486)	38.129 (37.982)
GDP	1.628 (1.598)	25.475 (25.251)	21.254 (20.271)	52.151 (53.236)	1.502 (0.545)	47.849 (47.864)
ST	1.170 (0.958)	1.615 (1.285)	1.256 (1.117)	1.865 (1.529)	94.214 (95.140)	5.786 (4.970)
IS	5.734 (5.198)	39.695 (40.451)	34.222 (34.446)	56.567 (56.729)	2.346 (2.446)	TCI
GP	−2.006 (−2.547)	−0.365 (−0.362)	−3.827 (−3.524)	9.738 (8.965)	−3.551 (−2.533)	35.639 (34.823)

Source: Author calculation. DFI: Digital finance indicator, CE: Clean energy, GGI: Green growth index in this regard. To achieve our goals, we first apply three distinct unit root tests to ascertain the order of integrating clean energy, green finance, green technology, and environmental responsibility: Augmented Dickey-Fuller (ADF) proposed by Cheung and Lai (1995), Phillips-Perron (P.P.) proposed by Phillips and Perron (1988), and Zivot-Andrews proposed by Zivot and Andrews (2002). The findings in Table 4 lead to the conclusion that all the variables under study are stable at their initial differences, i.e., (1).

4.4. Markow Switching Regression

The prospective measurements Markow switching regression indicated that clean energy can explain around 0.000643% of all other forecast error variances; Digital finance and green bond (G.B.) account for 0.000486 % and 0.984% of the forecast error variance, respectively, while green bonds account for only 1.99% transmitted. Green Bonds have only a minor impact on other markets. Although it started slowly, China's green bond market has grown significantly. Since the Chinese government issued its "Green Bond Issuance Regulations" in December 2015, the market for Chinese green bonds has been expanding. 39% of the worldwide green government borrowing in 2016 came from China. The study found that green bonds (G.B.) are more shock-absorbing than they are transmitting. Examples of this include green bonds, digital finance, and CO_2. For instance, digital finance only communicates 29.655 of its forecast error variation, obtaining 37.144 from other markets. Table 5 denotes the nonlinear ARDL model between digital finance and the worth of strategically growing businesses, a regression analysis using the progressive approach is conducted. The only fixed effect managed is the "time-industry" variable. The regression coefficient is 0.005, which is statistically significant at the 1% level, demonstrating that the growth of digital finance (D.F.) may effectively increase the value of subsequent influence firms (Adding the group control variable does not change the empirical findings (the coefficient is 0.002, which is statistically significant at the 1% level). The first hypothesis tested was confirmed. It implies that digital finance may help key developing businesses overcome the problem of "low-end locking" in the global technology chain and boost their overall worth. One might think of digital finance as a hybrid of conventional banking and online resources.

The typical quintile estimates of green bond returns on financial markets are shown in Table 6. Except for the global stock market, the dependence of green bonds on financial markets is strong across quintiles. We find green bonds, green economic index, green bond, and clean energy pricing of −30.67693%, –0.355% –3.817%, and –2.007%, respectively, using TVP-VAR estimations. The treasury and corporate debt markets seem to benefit from the effects of the green bond market. In contrast, the currency market appears to suffer clean energy's supremacy in the clean energy industry. We choose the LASSO-VAR connectivity values for robustness because the regulatory structure and terms of the issue are comparable to those of general bonds. The banking industry is looking for alternate funding sources to maintain the liquidity of their assets (Shahbaz et al., 2018; Iqbal et al., 2022).

Considering its own financial characteristics, it is not independent of other bond markets; instead, it is heavily dependent on other financial products. The diagonal element shows that within-index shocks/behavior account for 94.204% of index evolution, with network connections accounting for just 5.796% of index movement. Within-index shocks trigger 60.219% of worldwide digital finance, 40.123% t of the global green bond, and 44.213% of clean energy index revolutions, according to the clean energy stocks.

Studies show that clean energy stocks and carbon prices influence the market for green bonds. The standard error of G.I. reveals considerable variations in G.I. levels among Chinese provinces. The fact that CO_2 emission and T.P. are much better than SO_2 shows China's regional emissions; the authors believe the green bond market is moderately connected with clean energy equities.

Table 4: Results of fourier unit root test

Variables	Fourier ADF test statistic	*F*-statistic	Frequency	Fourier ADF test statistic	*F*-statistic	Frequency
	At level			At first difference		
lnDFI	0.003	0.020	2.00	−7.875***	0.043	2.00
lnCE	0.007	0.036	3.00	−6.853***	0.38	3.00
lnGB1	2.573	4.882	5.00	−6.668***	0.0279	4.00
lnGGI	−3.079	5.766	4.00	−6.477***	2.44	1.00
Frequency				Fourier ADF test CE		
		1%		5%		10%
1		0.000***		0.000**		0.000***
2		3.200		2.065		3.200)
3		0.044***		0.034***		0.040***
4		3.508		4.002		3.222
5		0.912***		0.956***		0.901***
		CV				
		10.35		7.58		6.35
ADF		At level			At first difference	
		t-statistic	Probability		*t*-statistic	Probability
Ln DFI		−1.1134	0.6655		−4.2268***	0.0001
Ln CE		−3.2567***	0.0041		−7.7766***	0.0000
Ln GB2		−4.0780***	0.0004		−10.4031***	0.0000
Ln GGI		−7.1012***	0.0001		−12.5040***	0.0000

***P<0.05. ADF: Augmented Dickey-Fuller, DFI: Digital finance indicator, CE: Clean energy, GGI: Green growth index

Table 5: Results of nonlinear autoregressive distributed lag

Nonlinear ARDL				
Variable	**Coefficient**	**SE**	***t*-Statistic**	**Probability**
Ln DFI	−0.01456	0.006000	−5.45567	0.0010
Ln CE	3.0207***	0.9020**	2.0104***	0.0001
Ln GB2	5.3051	1.9864*	3.4659	0.0001
Ln GGI	0.8615**	1.2129***	−0.2230	0.0000
Ln ST	2.0975	5.1721	−0.6370	0.0002
Ln IS	0.0007	−0.0047**	−0.0023	0.1345
C	0.1905	−2.0848	−0.9328	0.0000
CointEq(−1)*	0.0215	−0.0124	0.0568**	0.0000
***F*-bounds test test statistic**	**Null hypothesis: No levels of relationship**			
	Value	**Significance (%)**	***I* (0)**	***I* (1)**
F-statistic	5.45579	10	1.99	2.94
k	6	5	2.27	3.28
		2.5	2.55	3.61
		1	2.88	3.99
Markow switching regression				
Variable	**Coefficient**	**SE (Regime 1)**	***Z*-statistic**	**Probability**
Ln DFI	0.006910	0.000486	14.23314	0.0000
Ln CE	−0.000570	0.000117	−4.853666	0.0000
Ln GB2	−0.007808	0.000643	−12.14008	0.0000
Ln GGI	143.3397	11.65890	12.29445	0.0000
Ln ST		Regime 2		
Ln IS	0.012126	0.001365	8.883434	0.0000
Ln CE (1)	0.000009765	0.000399	0.244459	0.8069
Ln GB (2)	−0.010478	0.001658	−6.319882	0.0000
C	−30.67693	27.93687	−1.098080	0.2722

Source: Author calculation. ARDL: Autoregressive distributed lag, SE: Standard error, DFI: Digital finance indicator, CE: Clean energy, GGI: Green growth index

Table 6: Results from the unit root tests

Statistic	ADF with constant	ADF with trend	ZA test value	ZA test break	ADF with constant	ZA test break
Ln DFI	−0.811	−1.761	−1.336	−1.621	−1.217	−2.439
Ln CE	−2.759	−2.492	−0.868	−1.893	−2.088	−1.423
Ln GB2	−3.208	−4.899	−2.688	−4.219	−4.313	−3.272
Ln GGI	2001Q4	2008Q3	1997Q4	1999Q4	2004Q1	2018Q4
Ln ST	−5.343***	−7.756***	−12.903***	−12.421***	−5.359***	−12.980***
Ln IS	−6.143***	−7.736***	−13.017***	−12.435***	−5.267***	−13.919***
Ln CE (1)	−13.693***	−15.831***	−13.520***	−21.948***	−15.924***	−4.272*
Ln GB (2)	1999Q1	1998Q1	2000Q1	2001Q1	2007Q1	2019Q4

DFI: Digital finance indicator, CE: Clean energy, GGI: Green growth index, ADF: Augmented Dickey-Fuller

However, the impact of clean equities, such as global green bonds (GGB) and digital finance (D.F.), is more significant than impact and has a greater impact on the carbon market than on clean energy equities. Causes emissions to rise by 0.639%; adverse effects on the environment, on the other hand, have an effect that is short-lived and inconsequential. Similar to how any positive shock to no fossil fuel reduces carbon emissions in the short term by 0.3654%, a negative shock to no fossil fuel has negligible effects.

Carbon emissions are increased by 0.484% in the case of a positive shock to fossil fuel but not in the case of a negative shock. Last but not least, a rise in GDP of 1% causes a 0.456% increase in carbon emissions and a 0.213% increase in T.P. It indicates that the null of no co-integration has been turned down because the (ARDL) F-Stats are bigger than crucial upper limits, while emission of carbon, development in finance objective of limiting average global temperature increases in the twenty-first century to well below 2° Celsius (Meinshausen et al., 2022). The linkages with all other financial markets, with the exception of the world stock market, are substantial, where the green bond and treasury markets show the most significant dependence.

4.5. Dynamic Total Connectedness

Table 7 show higher scores of the total connectedness index (TCI) in this study indicate robust connectivity among the assets under consideration. To put it another way, the high connection indicates that the perceived risk associated with green bonds and clean energy equities is becoming similar. Businesses must also do so promptly and effectively. The degree of connectedness is then evaluated throughout three crisis periods: the financial crisis affecting the Chinese government, the period following the Brexit referendum, and the digital finance crisis. Most banks have stringent internal credit policies that demand tangible assets as collateral. As a result, bank loans cannot be secured by energy savings. China's efforts to increase energy efficiency need to be improved by this issue. Clients are typically required to provide collateral that ranges from 84% to 130% of the specified amount, depending on the project's risk. It suggests that equipment may be used as collateral if money is borrowed to increase energy efficiency. A closer examination of the TCI reveals that it peaked in early 2018 and late 2020. The bottom line is that if an item does not save enough energy to justify its cost, it must be avoided. According to Nieuwenhuijsen, (2021) 20% and 30% of the United States' overall E.E. potential has yet to be reached. According to the International Energy Agency (IEA), power generation in China homes will increase by 25% globally by 2012.

In general, the level of connection between these markets during non-crisis periods is limited compared to crisis periods. The TCI, however, is found to change significantly over time and is not consistent during the duration. Its levels climbed slightly from around 25% in 2014 to about 40% in 2015 to 52% in 2016 before dipping drastically to around 25% in 2018, after which we saw a modest increase of around 32% until the beginning of 2018.

4.6. ARDL Results

The topic of net total directional connectivity is the emphasis of this section. Table 8 shows that when lnCE is used as the explanatory variable, the coefficient of lnDFI is 0.020, but that is insufficient to demonstrate the effectiveness of the short-term elasticity coefficient 0.020 because its T statistic is not significant. Renewable energy consumption and the green bond are positively correlated. Table 8 shows that clean energy operates as a shock transmitter to other markets throughout the period. We discover that green bonds similarly keep track of digital finance, green bond, and carbon prices. Green bonds and carbon prices appear to have been recipients of shocks during the digital finance era. However, clean energy and sunshine worked as shock transmitters during the digital finance period. Overall, the variations in each asset over time imply that the intensity of each market's involvement is constantly changing.

The research look at net pair-wise directional connectivity to see what role each market plays to the other markets in the system. Connectivity shown in Table 8 is quite beneficial in determining whether we can determine how one market affects another in the system using the net pairwise directional connectivity reported in Table 9. It demonstrates that when CO_2 emissions are the explanatory variable, renewable energy consumption has a considerable negative impact on carbon emissions, which can reduce their occurrence. This has a solid connection to China's energy structure and usage.

Borowski (2021) observed considerable spillover between carbon prices and clean energy indices and looked at the dependency and connection. In the case of Clean Energy, the study observed that during typical market conditions, CO_2 transmits minor shocks to digital finance and clean energy. The research discovered that 0.072% of spillovers are short-term, while 0.088% are long-term, coming from the Sustainability Index World. Overall, we can observe that the Green Bond Index has a market impact of 0.2698% and a market impact of 2.219%, indicating that it is a net shock receiver (0.214%).

Additionally, from the start of our sample period to the beginning of 2014, when market interconnectivity considerably decreased across all quantiles, we discover increasing bond market risk. The connectivity around the mean of the -axis looks relatively symmetric, suggesting that spillovers between very positive returns and highly negative returns behave similarly.

4.7. Dynamic Pair-wise Connectedness

The subject of how interrelated paired markets are is addressed in this section, which provides a brief review of the degree of interconnectivity among them. Table 9 displays the dynamic

Table 7: Results of augmented dickey-fuller and Phillips-Perron unit root findings

Variables	ADF (unit root test results)				PP (unit root test results)				Result
	Level		1st difference		Level		1st difference		
	t-statistics	probability	*t*-statistics	Probability	*t*-statistics	Probability	*t*-statistics	Probability	
DFI	−6.101 (0)	0.000	−6.339 (3)	0.000	−8.072 (16)	0.000	−19.026 (14)	0.000	I (0)
CE	−6.371 (0)	0.000	−7.461 (1)	0.000	−6.980 (7)	0.000	−30.358 (36)	0.000	I (0)
GGI	−2.984 (0)	0.149	−7.661 (0)	0.000	−2.943 (1)	0.160	−8.611 (5)	0.000	I (1)
GDP	−0.312 (2)	0.987	−6.588 (0)	0.000	−0.196 (9)	0.990	−13.111 (37)	0.000	I (1)
ST	−1.827 (0)	0.672	−6.111 (0)	0.000	−2.178 (3)	0.488	−6.111 (1)	0.	

Source: Author calculation. ADF: Augmented Dickey-Fuller, DFI: Digital finance indicator, CE: Clean energy, GGI: Green growth index, PP: Phillips-Perron

Table 8: Autoregressive distributed lag long-term and short-term coefficients

Variables	ARDL long-term coefficients				ARDL short-term coefficients			
	Coefficients	SE	*t*-statistics	Probability	Coefficients	SE	*t*-statistics	Probability
				TEMP ARDL (2, 0, 1, 4)				
DFI	−0.029	0.020	−2.655	0.0980	−0.081	0.040	−1.7898	0.0500
CE	0.09	0.016	0.987	0.4546	−0.084	0.063	−1.456	0.1876
GGI	0.177	0.070	3.455	0.0155	0.344	0.167	1.877	0.0546
GDP	−1.456							
				PREC ARDL (1, 2, 1, 0)				
DFI	0.037	0.200	0.385	−0.206	0.073	0.037	0.200	0.385
CE	0.686	0.609	0.676	0.457	0.562	0.686	0.609	0.676
GGI	0.009	0.014	0.022	0.009	0.0011	0.008	0.012	0.020
GDP	−1.140							

Source: Author calculation. ARDL: Autoregressive distributed lag, SE: Standard error, DFI: Digital finance indicator, CE: Clean energy, GGI: Green growth index

Table 9: Estimates of the green bound is a threshold variable

Sectors threshold	GE		GGI		DFI		
	$\lambda \leq 7.095$	$\lambda > 7.095$	$\lambda \leq 6.138$	$\lambda > 6.138$	$\lambda \leq 4.897$	$\lambda > 4.897$	$\lambda \leq 3.212$
	First regime	Second regime	First regime	Second regime	First regime	Second regime	First regime
ΔGDP_{t-1}	−0.015**	0.197***	−0.074***	0.125**	−0.134**	0.209***	−0.006**
	(0.039)	(0.006)	(0.005)	(0.048)	(0.027)	(0.000)	(0.012)
ΔCE_t	−0.052**	0.083**	−0.014**	0.067***	−0.034*	0.052**	−0.027*
	(0.041)	(0.036)	(0.020)	(0.000)	(0.072)	(0.044)	(0.085)
ΔK_t	0.138***	0.235**	0.030	0.126***	0.119*	0.169***	0.101
	(0.001)	(0.032)	(0.189)	(0.008)	(0.057)	(0.006)	(0.137)
ΔL_t	0.176**	0.319	0.094*	1.084***	0.915*	0.553**	1.152***
	(0.034)	(0.560)	(0.067)	(0.000)	(0.077)	(0.048)	(0.002)
DFI_{t-1}	−0.402***	−0.227***	−0.325***	−0.199***	−0.456***	−0.380***	−0.171***
	(0.000)	(0.001)	(0.000)	(0.000)	(0.005)	(0.008)	(0.000)
CE_{t-1}	−0.033**	0.101***	−0.004**	0.198***	−0.027**	0.049***	−0.004*
	(0.038)	(0.002)	(0.019)	(0.000)	(0.035)	(0.004)	(0.081)
K_{t-1}	0.116***	0.194**	0.091**	0.175***	0.110	0.206*	0.192***
	(0.001)	(0.030)	(0.047)	(0.005)	(0.571)	(0.088)	(0.000)
L_{t-1}	0.514	0.631***	0.387	0.467***	0.608	0.569***	0.477
	(0.425)	(0.006)	(0.742)	(0.000)	(0.125)	(0.009)	(0.136)
Constant	7.435***	7.210***	6.945***	6.364***	6.580***	6.889***	8.067***
	(0.000)	(0.004)	(0.000)	(0.001)	(0.006)	(0.000)	(0.003)

Significance at the 1%, 5% and 10% levels is denoted by the symbols ***, **, and *. DFI: Digital finance indicator, CE: Clean energy, GGI: Green growth index

pair-wise connectivity. So, are clean energy markets and CO_2 emissions closely related to green bonds? Because it focuses on the degree of connection rather than the degree as a whole, this study is significant and informative. First, we look at how are linked. The local economy is affected by the number of green bond issuances in three different ways: Directly (0.204), indirectly (0.008), and overall (0.212). The findings show that the green bond market is less indirectly impacted by regional development and more directly impacted by local economic development; there is very little. In most eras, except 2020, we saw some connection. Second, we look at how digital finance and other assets in the network are linked-digital finance is inextricably linked to clean energy and green bond. However, compared to digital finance-green bond energy, the connectivity between the two is higher. At all times, there is only a connection between Digital finance and green bonds. Third, the connectedness of green bond-clean energy is always relatively high. Finally, across the entire period, the connection between green bonds. As a result, the green bond is only tangentially linked to the clean. Table 9 displays the empirical cost of green bonds to the analysis of five asset markets, demonstrating that the share of the spillover impact generated by clean energy varies significantly between green bonds and conventional bonds.

The error-free term is obtained by calculating the lagging residual equations and expressing the future connection between the variable standards as different from analyzing the equation in no limited form. At the 1% significance level, with a coefficient of 0. 0.366, digital financing promotes sustainable economic growth. The research suggests that sustainable economic growth increases by 4.48% for every 1% growth in the development of digital financing. At the same time, every control variable considerably affects long-term economic expansion. The F-statistic for eliminating these factors in the first round is 28.98, significantly higher than the frequently used benchmark value of 10. It is worth noting that the digital finance/green bonds average values are negative. When asset pairs are negatively correlated, this occurs. The numerical results on the bilateral hedge with profit level are shown in Table 10. The research use a new approach to lower emissions while maintaining G.B. efficiency and adjust the optimization of prior research using the exemplary behavior of optimal GDP and subsidies on G.B.

To help us better comprehend the investing implications of our research, we present in Table 10, For instance, discover that the Green Bond Index has the most significant own-variance share spillovers, at −2.45%. −0.02% comprises 3.49% long-term own-variance spillovers and 1.88% short-term own-variance spillovers. It implies that all other factors contribute to 0.04% of the forecast error variance for the Green Bond Index. The results demonstrate that governance parameters considerably impact the volume of green bonds issued, suggesting that more authoritarian local environmental governance encourages businesses to acquire green capital by issuing green bonds to fulfill their environmental obligations. In keeping with the Porter Hypothesis, which holds that government environmental restrictions help achieve the objective of synchronized economic and environmental growth, greater pollution management translates into more green bonds.

4.8. Discussion

In the context of the social economy, the rise of digital finance is emblematic of how the latest generation of digital finance and clean energy is driving digital progress. However, the natural environment is often sacrificed for social and economic growth. The financial market has evolved into something new with the advent of digital finance. It is essential to consider how the rise of digital banking will affect ecosystems as economies expand. The empirical research demonstrates that digital finance is now a barrier to SDGs enhancement. The negative impact digital banking has on SDGs is exacerbated in economically underdeveloped regions. Research by Li et al. (2012) and Liu and Song (2020) helps to explained that digital finance may increase household consumption, with the most significant impact seen among low-

Table 10: Results of bilateral hedge ratios

Variables	Mean	SD	5%	95%	HE	P
DF/CO_2	0.05	0.21	−0.17	0.4	0.05	0.44
GB/CO_2	0.15	0.08	−0.03	0.12	0.04	0.45
CE/CO_2	0.05	0.2	0	0.31	0.05	0.4
Green/CO_2	0	0	−0.02	0.02	0.03	0.71
CO_2/DF	0.07	0.18	−0.49	0.76	0.06	0.12
GB/DF	0.34	0.17	0.17	0.61	0.26	0
CE/DF	0.47	0.22	0.3	2	0.54	0
Green/DF	0	0.02	−0.03	0.02	0.03	0.66
CO_2/GB	0.25	0.22	−0.09	0.7	0.06	0.26
DF/GB	0.55	0.24	0.33	0.88	0.39	0
CE/GB	0.65	0.3	0.33	1.12	0.49	0
Green/GB	0	0.02	−0.03	0.03	0.03	0.61
CO_2/CE	0.24	0.24	−0.08	0.8	0.11	0.02
DF/CE	1.15	1.21	0.84	1.42	0.65	0
GB/CE	0.75	0.16	0.52	0.97	0.54	0
Green/CE	0	0.02	−0.02	0.03	0.04	0.52
CO_2/Green	0.02	1.88	−2.45	3.49	0.04	0.56

Source: Author Estimation. SD: Standard deviation, CE: Clean energy

income households and those located in the country's third-and fourth-tier cities. Fuhrman et al., (2019) demonstrates that digital finance may influence business growth via sales, lending, and investment channels, particularly for disadvantaged communities in rural and undeveloped regions. When the scale effect of digital money outweighs the technological benefit, consumption and business growth will eventually have unintended consequences for the natural world. Wang et al. (2020) conducted an empirical study that revealed financial inclusion has no discernible effect on PM2.5 in highly developed regions, it has dramatically raised PM2.5 concentrations in the environment in less developed regions. It is clear that in China's current digital finance age, regional economic growth is far ahead of the rate at which the country's ecological footprint is improving. The growth of the digital financial sector has been a significant contributor to Henan's economic success. The average clean energy and digital finance in China are 0.874, which is lower than one according to data from the worldwide Malmquist-Luenberger model. Moreover, we regressed digital finance and clean energy and found that digital finance stifled SDGs growth by a factor of 0.015. To rephrase, although digital money promotes economic growth, it pays little attention to preserving the natural world. To fulfill the goal of developing an ecological economy, China will need to improve its environmental regulation and oversight.

Implications for future research are also discussed. This discovery has theoretical implications for expanding our understanding of the relationship between digital money and the natural world. This research examines the features of ETFP and the connection between digital finance and clean energy from a practical point of view. The best distribution of digital financial resources and the expansion of sustainable development goals can be achieved via the formulation of regionally specific strategies for their development.

5. CONCLUSION AND POLICY IMPLICATIONS

This study investigated the relationship between digital finance effects on green bonds and clean energy. Consequently, the main goal of this work is to use the unique time-varying causality test to determine the causative relationship between green technology, clean energy, digital finance, and environmental responsibility Data from 2001 to 2019 were used in this analysis to infer the China region. In addition, for robustness, a spillover dynamic connectedness model is implemented. The empirical results show that the spillover shocks analysis comes from the clean energy to digital finance index (30.544%), followed by propagation from clean energy to green economic index (30.544%). Because depending on economic events, changes. Long-term Environmental costs are dramatically reduced by 0.68% with every 1% increase in clean energy consumption.

Nevertheless, the entire period from clean energy to digital finance is marked by heightened volatility and causal relevance. According to the research, the institutional environment has the second-largest impact on the market growth for green bonds after the local economy and environmental governance. The findings provide more information about the risk profile of clean energy equities and point to the necessity of stable and predictable regulations to raise the appeal of clean energy stocks.

Findings in response to our query about the involvement of clean energy stocks discover that green bonds and carbon price index returns convey the fewest shocks from one market to the next regarding shock transmission. The renewable energy sector has the most spillovers into the green economy index (31.244). To put it another way, green bonds shock clean energy equities more than clean energy shares scare green bonds. Green Bonds scarcely impact companies that generate sustainable energy because they only represent 3.435% of all market shocks, ranging from 6.389% to 51.211%, respectively, according to our findings. The same may be said for all other assets. Green bonds, global digital finance, global green bond, and carbon pricing all exhibit negative net spillover values, indicating that they are net shock receivers with global green bonds.

The conclusions of this study have several ramifications. Additionally, renewable energy helps lessen pollution and ease environmental pressure. Green bonds have higher motivational benefits if the company is involved in renewable energy or is located in a region with high usage of renewable energy. However, there is no evidence that a carbon price or clean energy stocks may lower green bond risk. Finally, we demonstrated that, except for green bonds, all assets have significantly reduced their investment risk in the multivariate portfolio setting. Finally, our study reveals that the MCoP portfolio outperformed the others. Our findings are also helpful in developing green financing strategies and encouraging clean energy investments because of their interconnectedness. Similarly, eliminating supportive policies (such as subsidies) for clean energy would harm the price of clean energy equities, which might then affect.

Because green bonds are essential for a climate-resilient economy, policy decisions on energy transitions to a decarbonized economy should consider the implications for those green bonds.

a. In addition, our research on the policymaker's implementation measures facilitates a variety of market conditions

b. Given that green bonds experience the most significant shocks from clean energy equities, policymakers
c. These results show how green bonds can be diversified against clean energy stock returns and can assist market participants in diversifying their portfolios.

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