Financial Technology's Role in Sustainable Development: An ESG Perspective

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ABSTRACT

With an integration of Financial Technology (Fintech) and Environmental, Social and Governance (ESG) principles, the global financial landscape is undergoing with a rapid transformation. This following research paper explores how Financial Technology can drive sustainable development through an ESG framework with a particular emphasis on Indian Context. As the financial markets evolve, the need of aligning the technological innovation with sustainability goals has increased to foster responsible economic growth.

This study examines the role of fintech in enhancing financial inclusion which includes the promotion of green finance and advancing energy efficiency and how the three crucial components contributing to sustainable economic practices. By leveraging both qualitative and quantitative research methods, the study identifies key trends, opportunities and challenges in the adoption of Fintech solutions to support sustainable development goals (SDGs). It investigates that how digital financial services, blockchain, artificial intelligence and other technological advancements can facilitate ESG-aligned investments, improve transparency and encourage responsible corporate behaviour. In the Indian context, where financial inclusion and green finance are emerging priorities, Fintech is offering the transformative potential by bridging gaps in accessing to financial services, optimizing resource allocation and enabling efficient capital mobilization for sustainable projects. However, the regulatory challenges, data security concerns, and the requirement of robust policy frameworks will always remain a significant hurdle.

The findings of this research paper provide valuable insights regarding how the disruptive innovations in finance can integrate with the rising demand for ESG compliance. By integrating sustainability-driven Fintech solutions, financial systems can become more resilient, responsible and inclusive, ultimately fostering long term economic growth while addressing global sustainability challenges.

Keywords: Financial Technology (Fintech), ESG, Sustainable Development, Green Finance, Digital Transformation, Regulatory Framework, SDGs.

INTRODUCTION

For achieving the SDG goals (Market Shocks and Stock Volatility, n.d.). by 2030, the UN has adopted 17 Sustainable Development Goals (SDGs) in 2015 by laying out a global agenda to address a wide range of obstacles like poverty, inequality, and environmental degradation. These Sustainable Development Goals cover a wide range of goals that, to address complex global challenges, call for coordinated actions across several industries and geographical areas. But even with the SDGs' comprehensive road map, reaching these goals has proven to be a difficult undertaking. There has been uneven global progress toward these goals,

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and multiple studies have pointed out significant obstacles that stand in the way of achieving their full potential. (Naysary, 2024)

According to research by 2030, only 54% of nations are expected to have met all of the Sustainable Development Goals (SDGs), up from 43% in 2015. This means that 15% of countries may not have met the goals., discovered that there is still room for development even among high- and middle-income nations in the OECD and Europe, further supporting this slow growth. These worries were also expressed by, those who noted that few SDGs are progressing as intended and that many are really regressing or moving backward.

This was glaringly highlighted in the (2023) annual sustainable development report, which reported that the global SDG index had declined and that the world had failed to achieve progress toward the SDGs for the second year in a row. This sudden drop from 2020 demonstrated that it requires more work to completely understand the hurdles to prevent the sustainable development, as the current efforts will not be enough to completely fulfil the 2030 targets.

With regards to this, the financial sector has come in the light for promoting the socio-economic changes and to resolve the issues related to sustainable development. In this case the banking industry has played a most important role in advancing equality, reducing poverty, and encouraging more economic growth over the years. The advent of Fintech has observed a gigantic shift in the international finance, and it has given sufficient solutions with huge potential for fostering sustainable development.

Fintech has brought radical shifts in the distribution and exhaustion of financial services, making them more attainable, capable and comprehensive. The new literature on the interaction between Fintech and sustainable development can be generally classified into two streams. The first stream addresses the spillover impact of Fintech on sustainable development, especially through its function in driving financial inclusion. Financial inclusion is a key driver of economic growth and social mobility, and Fintech has been recognized for its potential to bring financial services to poor and unbanked communities.

Moreover, FinTech has been connected to growing social justice by reducing the hurdles that generally diminished groups face when trying to approach finance. FinTech promotes more economical and appropriate financial service distribution by optimizing digital platforms. It also facilitates easy accessibility of people and small business to improved financial services can enhance lives, reduce, poverty and advance sustained economic development. In addition, the ability of Fintech to collect and examine large data pools enables highly individualized financial offerings, making their financial inclusion as well as its positive social impacts, possible.

The second line of investigation examines the exact connections between Fintech and specific results tied to sustainable development. This research investigates how Fintech can advance sustainability in various sectors such as small and medium sized enterprises (SMEs), health, energy efficiency, green finance and agriculture. For instance, studies have explored how Fintech can assist in funding green projects, maximise energy consumption and increase productivity in various sectors. Based on this study, Fintech can play a crucial role in sustainability by maximising processes, reducing costs and increasing the overall effectiveness of resource utilization.

Fintech for example has greatly enhanced the quality and accessibility of health services particularly in disadvantaged segments of the healthcare system. Fintech reduces the time and cost associated with accessing medical care by making the provision of healthcare services to far-flung locations using digital payment systems and mobile platforms. Fintech has also facilitated the easier creation of innovative financial solutions in the agricultural sector, making it easier for farmers to manage risks, access finance and improve productivity. By promoting resilience and enhancing the quality of life for smallholder farmers, these innovations contribute to the overall sustainability of the agricultural sector.

Whilst the optimistic potential for Fintech to realize sustainable development is high, its connection to sustainability is nuanced and multifaceted. Most of the available literature is based on a panel data analysis framework that investigates this connection by using several metrics and indices to represent the dynamics between Fintech and sustainable development outcomes. Although analysis of panel data

has much to contribute it entails also some difficulties regarding the availability of data comparability and the heterogeneity of context between and within regions and sectors. Understanding the directional interlinkages between Environmental, Social and Governance (ESG) companies and Fintech companies is an important research area in this area. Fintech and ESG markets are interlinked in a complex manner with Fintech capable of affecting and being affected by ESG trends. To address this complexity, modern studies have applied advanced analytical tools, such as wavelet analysis and dynamic conditional correlation models to analyse the relationship between Fintech and ESG companies and provide more realistic insights into how these interactions occur under different situations and time periods.

For instance, wavelet coherence analysis has been used to examine the co-movement of India’s Fintech and ESG indices, including S&P India Tech Index, MSCI India Domestic Financials, BSE 100 ESG index and NIFTY 100 ESG Leaders Index. The method detects lead-lag connections among Fintech companies and ESG based companies and ESG Based companies over various time horizons. In the same vein, dynamic conditional correlation models like the DCC-GARCH model have also been employed in the examination of time-varying correlations among FinTech and ESG markets in India, providing understanding of how the relationships change depending on economic situations.

LITERATURE REVIEW

The positioning of Fintech, on the cusp of finance and technology, to achieve sustainable development is growing in importance in India. In this literature review, numerous academic papers and empirical research have been taken into consideration showing that Fintech has the ability to drive sustainability concerns across diverse sectors. Its transformational capabilities and disruptive nature enable innovation to confront intricate economic, environmental and social challenges.

It accomplishes this through ensuring green finance and financial inclusion, promoting renewable energy projects and enhancing social welfare. The review article attempts to examine the role of Fintech in India’s overall sustainable development objectives. It examines challenges embedded in the dynamic nature of this field and provides potential directions for the future.

Fintech innovations have transformed financial inclusion in India immensely by utilizing mobile banking, UPI and digital credit scoring. Account penetration increased from 35% in 2011 to 80% fuelled by schemes such as Jan Dhan Yojana. Though there has been progress there are still gaps in rural and marginalized segments. Fintech facilities enhanced credit availability SMEs and informal sector entities through sophisticated algorithms that evaluate creditworthiness. Yet, privacy issues and digital literacy create challenges. In wealth management, Fintech lowers costs and broadens access, but financial literacy is an area of concern. Crowdfunding sites such as Ketto and impact investing models play a crucial role in catering to disadvantaged communities. Empirical evidence indicates a positive relationship between Fintech adoption and green finance programs. Fintech assists Indian banks in evaluating sustainable business models, green lending and ESG investments. Digital technologies drive environmental sustainability by cost-efficient green investments

influencing green growth and environmental indicators. In addition, there is a two-way relationship between Fintech innovation and green finance, emphasizing Fintech in ensuring environmental sustainability.

The intersection of Fintech and the energy sector in India increases efficiency and sustainability. Fintech promotes energy efficiency among renewable energy companies and cities. Green finance, facilitated through Fintech, facilitates India's shift towards sustainable energy resources. In addition to environmental taxes and policies, Fintech promotes the use of energy-efficient technologies and sustainable energy resources. Academic literature points out Fintech's capability to transform sustainable development factors such as economic development, financial inclusion, green investment and climate change mitigation. Contend FinTech increases financial inclusion, which is pivotal for India's SDGs. Creating digital infrastructure and regulatory environments can unlock Fintech and financial development in India during 2000-2019. Employing Quantile Regression, they conclude that Fintech and industrial growth have a negative effect on environmental sustainability across all quantiles, whereas green innovations and financial development promote sustainability. Secondary analysis of data by assesses the contribution of Fintech in reducing Fourth Industrial Revolution threats. Results indicate that the use of FinTech to promote financial inclusion can improve firm and household climate shock resilience such as increased weather and sea-level rise. Insurance, savings, credit and mobile payments using FinTech support climate-exposed groups. Systematic literature review by identifies Asian digital financial inclusion trends. The research discovers India's swift FinTech uptake alleviates poverty but also uncovers gender and income disparities in digital financial inclusion analysing the interactive impacts of green finance and FinTech-enabled energy technologies support a greener economy, with two-way causality between CO2 emissions and green finance. A fascinating study delves into Paytm's "Green Initiative" wherein users perform environmentally friendly actions such as reducing paper usage, walking or online transactions to earn rewards. The initiative has enhanced carbon reduction and improved financial literacy in India's urban and semi-urban markets.

LITERATURE REVIEW OF METHODOLOGICAL APPROACHES

This section discusses three state-of-the-art methodologies gaining rapid importance due to their applicability and effectiveness in disentangling the complexities of the ESG and Fintech markets in India. Specifically, these are wavelet analysis DCC-GARCH models and connectedness analysis.

Wavelet analysis has emerged as an essential tool for analysing financial markets in India particularly assessing Fintech adoption and ESG investment trends. It provides a granular view of time-series data while retaining information about time and frequency, making it highly effective in India's dynamic financial environment. Used wavelet analysis to assess ESG driven stock performance offering investment insights. Similarly applied wavelet coherence analysis to evaluate ESG investments risk-hedging potential. In India, leveraged wavelet coherence to analyse Fintech expansion, uncovering lead-lag relationships that traditional methods miss. This method is beneficial for capturing evolving ESG and Fintech market patterns in India's volatile economy handling nonlinear relationships and ensuring data size independence.

The DCC-GARCH model is crucial for modelling time-varying correlations and volatilities in India's interconnected ESG and Fintech sectors. Originally developed by Engle, this model has been widely used in financial studies. For instance, employed it to examine dynamic volatility in ESG indices. Likewise, applied it to assess the interconnection between ESG stocks, green bonds and renewable energy indices. In India's Fintech sector, utilized DCC-GARCH to study volatility spillovers.

EMPIRICAL RESULTS

1. Data Description

To study the stock market performance of ESG and Fintech indices, we employ the daily prices of the two ESG Leaders Indices: (i) NIFTY 100 ESG Leaders and (ii) BSE 100 ESG Index. Both indices are free-float and market capitalization-weighted, designed to provide the performance of companies selected from a parent index based on ESG Standards. This filtering process includes the exclusion of firms that operate in specific business lines, as well as of ESG ratings and ESG-related controversy exposure. In presenting firms that lead on ESG practices in their corresponding industries, such indices provide the best instruments for evaluating the financial performance of sustainable business strategy. The selection of both NIFTY 100 ESG Leaders and BSE 100 ESG Index provides a wider geographic exposure including firms from India.

The Fintech indices, however, utilize the daily price history of two indexes: (i) S&P India Tech Index and (ii) MSCI India Domestic Financials. These indexes reflect the performance of firms at the leading edge of this change on the Indian horizon. An analysis of these indices tells us about the effect of technological innovations on the financial sector and investor sentiment. Both ESG and Fintech indices are from NSE database. The sample interval is from March 13, 2020, to March 13, 2025. Using indices from the NSE database guarantees access to high-quality, in-depth data supporting rigorous empirical analysis. The long sample period also allows for the investigation of short-term dynamics and longer-term trends. Having chosen indices that represent different but increasingly overlapping sectors, our study is able to provide useful insights into comparative market performance, synergies and divergences between sustainable investment practices and fintech innovation.

The following figure presents and logarithmic returns for all series investigation in the research. The table presents the daily logarithmic returns summary statistics where NIFTY 100 ESG Leaders and MSCI India Domestic Financials have the maximum mean return while S&P India Tech Index possesses the minimum mean return. All of them exhibit negative skewness and substantially larger kurtosis than in the standard normal distribution. Last but not the least, all the Jarque-Bera statistics are significant.

2. Wavelet Coherence Evidence

The figure represents the estimated wavelet coherence and phase for all six pairs with one of the two Fintech indices and one of the two ESG indices. We have some interesting findings from the coherence figure. There are stronger regions or regions between the two Fintech indices (S&P India Tech Index and MSCI India Domestic Financials) and the two ESG indices (NIFTY 100 ESG Leaders and BSE 100 ESG Index), suggesting strong correlation across many periods and at many frequencies. But when it comes to the major areas between MSCI India Domestic Financials and the two ESG indices, the combined area is smaller than that of the two previous Fintech indices.

Another observation of interest is that major areas of Fintech indices are comparable to those of ESG indices. In addition, nearly all arrows are pointing towards the right which means that there is high positive correlation between the Fintech indices and the ESG indices. Lastly there are a substantial number of arrows pointing upwards (representing Fintech indices ahead of ESG indices) and a substantial number of arrows pointing down (representing ESG indices ahead of Fintech indices). This means that for certain dates and certain frequencies the Fintech indices precede the ESG indices. Since all these indices depict the performance of the stock markets are in general supposed to be efficient it is natural to expect one market type does not broadly dominate the other for all times and frequencies.

METHODOLOGY

1. Wavelet Analysis

Here we first briefly explain wavelet coherence analysis. The continuous wavelet transforms (CWT, Wnx(s)W_n^x (s)Wnx(s)) for a discrete time series xn, n=1, N with uniform time steps

At is defined as:

$$Wnx(s) = s\delta tk = 1\sum Nxk\psi 0 * (s(k - n)\delta t)$$

Where ψ0(t) is a given mother wavelet s>0 is the scaling factor which dilates the wavelet and n is the translation parameter that represents the location of the wavelet. Then we can define the cross wavelet transform (Wnxy(s)W_n^{xy} (s)Wnxy(s)) of the two-time series xn and yn as follows:

$$Wnxy(s)=Wnx(s)Wny*(s)$$

Where the superscript" *" represents the complex conjugate. Now the wavelet coherence (Rn2(s)R_n^2 (s)Rn2(s)) of the two-time series can be defined as:

$$Rn2(s)=S(s|Wnx(s)|2)\ S(s|Wny(s)|2)\ |S(sWnxy(s))\ |2$$

Where is a smoothing function. Here the phase difference is given by:

$$\phi nx(s)=\tan-1(Re\ (Wnxy(s))Im(Wnxy(s)))$$

Where Re () and Im() stand for the real and imaginary components of the complex cross wavelet transform. The phase is graphed in the coherence diagram by arrows. In case the two series are in phase or positively correlated the arrow will be pointing right and vice versa. In case the first series is ahead of the second the arrow would be pointing right up or left down. In the same way when the second series is leading the first, the arrow would be pointing left up or right down.

2. DCC GARCH Analysis

The Dynamic Conditional Correlation Generalized Autoregressive Conditional Heteroscedasticity (DCC CARCH) model proposed by is the generalization of the basic GARCH model in which Yt is a m×1m \times 1m×1 vector for representing m time series.

$$Yt=\mu+\epsilon t,\ \epsilon t=Ht1/2\eta$$

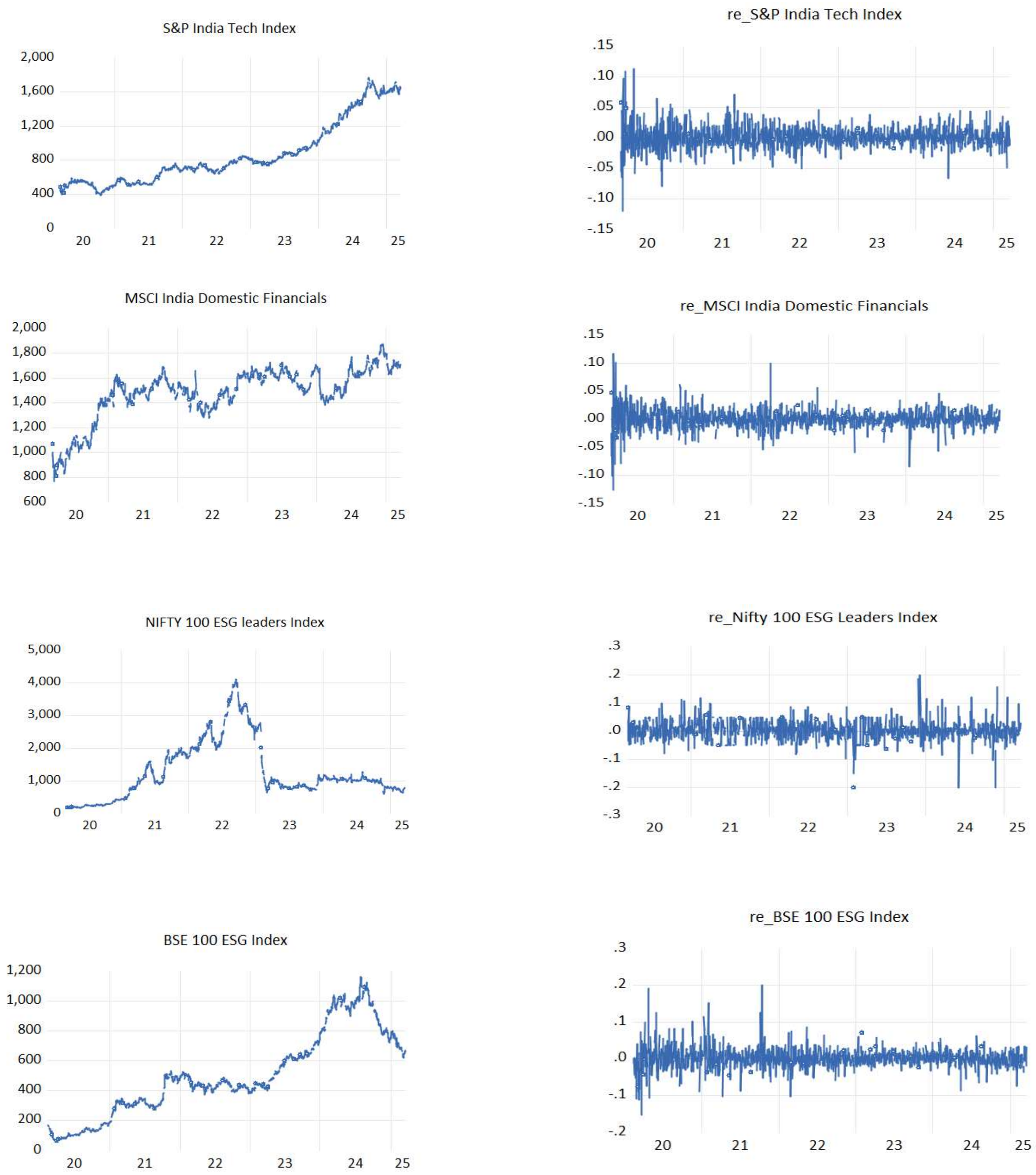
$$Ht=DtRtDt,\ Dt=diag(h11...,hmt)$$

$$Rt=Qt*Qt-1Qt*-1,\ Qt*=diag(q11t,...,\ qmmt)$$

$$Qt=G(1-\alpha-\beta)\ +\alpha(\epsilon t-1\epsilon t-1')\ +\beta Qt-1$$

Q_t and R_t are the covariance and correlation matrices respectively and G is the unconditional covariance matrix of the $D_t^{-1}\epsilon_t$. It is required that $\alpha > 0$ and $\beta > 0$ for the covariance matrix to be positive define. When $\alpha + \beta < 1$, the model is so-called mean reverting.

Graph -1:



Fintech Indices		
	S&P India Tech Index	**MSCI India Domestic Financials**
Mean	0.01042	0.0036
Std.Dev	0.0096	0.0271
Skewness	0.0306	0.6350
Kurtosis	2.481	4.031
Jarque Bera	0.252	28.04
Min	0.0062	-0.0635
Max	0.0662	0.1024

ESG Indices		
	NIFTY100 ESG Sector Leaders Index	**BSE 100 ESG Index**
Mean	-0.02027	0.001930
Std.Dev	0.05858	0.01355
Skewness	-1.4215	0.77776
Kurtosis	5.5914	3.6961
Jarque Bera	12.332	2.4202
Min	-0.2000	-0.0198
Max	0.0604	0.0384

3. Time Series Dynamics of the Co-movement

Using both the wavelet coherence and DCC GARCH we can get the time series estimate of the dynamic correlation between one of the Fintech indices and one of ESG indices. The time series of the dynamic correlations are shown. The unconditional correlations as well as the average value of the dynamic correlation from wavelet coherence and DCC GARCH for all pairs considered. Furthermore, the average dynamic (i.e conditional) correlations are higher for the DCC GARCH model compared to the wavelet coherence. This is also clear from where both dynamic correlation series fluctuate but the one from the DCC GARCH is higher than that from the wavelet coherence on the average.

4. Frequency Dynamics of the Co-movement

The wavelet coherence allows us to compute the average correlations over different frequencies by averaging the correlation across time for a given frequency. The correlations over different frequencies (scales) are plotted. Again, the behaviour of the correlation with respect to NIFTY100 ESG Sector Leaders Index is similar to the correlation with respect to BSE 100 ESG Index. It is clear from that the correlation is significant for almost all frequencies except for the frequencies around 256-day. For lower frequencies like 512-day the correlation increases.

5. Connectedness Analysis

The data provides the output from our connectedness analysis based which is a method used to measure the interconnectedness or spillover effects among different entities within a network. The analysis is based on a VAR (Vector Auto-regressive) model and computes how much of the forecast error variance of each entity can be attributed to shocks from the other countries.

The values in the main section of the table represent the percentage of forecast error variance in each row index attributable to shocks in each column index. For example, the cell at the intersection of the S&P India Tech Index row and the MSCI India Domestic Financials column, the value is 13.14. This means that 13.14% of the forecast error variance in S&P India Tech Index can be attributed to shocks from MSCI India Domestic Financials. Similarly in the intersection of the BSE 100 ESG Index row and the NIFTY 100 ESG Sector Leaders Index column, the value is 22.82. This means that 22.82% of the forecast error variance in MSCI Indian Domestic Financials is due to its own shocks.

The given statistical data for the S&P India Tech Index, MSCI India Domestic Financials, NIFTY100 ESG Sector Leaders Index, and BSE 100 ESG Index provide valuable insights into their financial performance and risk profiles. Starting with the mean returns, the S&P India Tech Index shows a positive mean return of 1.042% which indicates consistent profitability and steady performance in the Indian Technology sector. This indicates that the index constituents are enjoying digital innovation and sector expansion. In contrast, MSCI India Domestic Financials has a lower mean return of 0.36% suggesting low merging and possibly greater competition within the domestic financial sector. On the ESG side, the NIFTY100 ESG Sectors Leaders Index has a negative mean return of -2.027% which may reflect operational inefficiencies, economic decline or regulatory pressures facing sustainable investments. The BSE 100 ESG Index with an average return of 0.193% exhibits moderate but consistent performance and thus provides an attractive choice for cautious investors searching for long run ESG based investments.

Standard Deviations is one of the most prominent measures of risk which reflects price volatility. The S&P India Tech Index has a low standard deviation of 0.96%, indicating stability and lower risk and is a good option for conservative investors. The MSCI India Domestic Financials Index has a higher standard deviation of 2.71% indicating higher volatility consistent with the financial sector's exposure to economic conditions and policy shocks. The NIFTY100 ESG Sector Leaders Index boasts the largest standard deviation at 5.858% representing extreme volatility, perhaps due to unstable ESG policies or unreliable investor confidence. On the other hand, the BSE 100 ESG Index at 1.355% depicts moderate volatility as would be expected from a diversified ESG portfolio.

Skewness captures asymmetry in return distribution. The S&P India Tech Index has almost zero skewness (0.0306), indicating that returns are symmetrically distributed which lessens the chances of extreme fluctuations. The MSCI India Domestic Financials Index has positive skewness (0.6350) which indicates a higher likelihood of positive returns, implying that financials companies in this index will have good growth opportunities. But the NIFTY 100 ESG Sector Leaders Index is negatively skewed (-1.4215) indicating a higher tendency to experience large negative returns which may be caused by market shocks or sectoral risks. The BSE 100 ESG index, being positively skewed (0.77776) indicates greater possibilities of large gains and hence is more appealing to investors looking for high returns with some volatility. Kurtosis indicates the probability of extreme deviations. The S&P India Tech Index has a kurtosis of 2.481 which is near the normal distribution value of 3, reflecting relatively stable returns.

The MSCI India Domestic Financials Index has greater kurtosis at 4.031, reflecting that returns are more likely to be subject to extreme fluctuations possibly due to economic or regulatory shocks. The NIFTY 100 ESG Sector Leaders index is extremely leptokurtic (5.5914) suggesting the occurrence of extreme negative and positive returns which indicates a high-risk situation. The BSE 100 ESG Index with a kurtosis of 3.6961, suggests a moderate leptokurtic distribution i.e. moderate possibilities of extreme price movements. The Jarque-Bera test determines if returns are normally distributed. A low Jarque- Bera score of 0.252 for the S&P India Tech Index assures that its returns are normal and can be predicted. MSCI India Domestic Financials Index, however, has a high value of 28.04 indicating non-normal returns resulting from market turbulence and investor actions. NIFTY100 ESG Sector Leaders Index, at a Jarque-Bera of 12.332 also exhibits extreme differences from normality and hence poses greater risk for conventional investors. The BSE 100 ESG Index having a Jarque Bera value of 2.4202 reflects that it is nearer to normal distribution which presents higher predictability.

The minimum and maximum returns reflect extreme risk and reward possibilities. The S&P India Tech Index enjoys a minimum return of 0.62% confirming its strength whereas the MSCI India Domestic Financials Index has minimum return of -6.35% indicating high risk of the downward direction. The NIFTY 100 ESG Leaders Index enjoying a minimum return of -20%is indicative of very high sensitivity to market negatives. The BSE 100 ESG Index which has a minimum return of -1.98% offers greater downside protection and is therefore a safer ESG investment.

The S&P India Tech Index is a stable low risk investment opportunity with reliable returns based in this analysis. The MSCI India Domestic Financials index has growth potential but at a more volatile which is appropriate for aggressive investors who can accept uncertainty. The BSE 100 ESG Index offers a balanced risk-return profile which is appropriate for sustainable investing with moderate risk. These findings contribute significant depth to financial decision making and market analysis.

Table-1: Coefficient estimates of multivariate DCC GARCH.

	ESG indices	
	Coefficient	**Std. Deviation**
NIFTY100 ESG Sector Leaders Index		
α_{DCC}	0.06342	0.01327
β_{DCC}	0.9024	0.021842
Log. Likelihood	30.4755	0.0803
BSE 100 ESG Index		
α_{DCC}	0.06342	0.01327
β_{DCC}	0.9024	0.021842
Log. Likelihood	55.246	0.0175

	Fintech Leaders	
	Coefficient	**Std. Deviation**
S&P India Tech Index		
α_{DCC}	0.74031	0.05469
β_{DCC}	0.91595	0.022248
Log. Likelihood	44.123	0.0410
MSCI India Domestic Financials		
α_{DCC}	0.06342	0.01327
β_{DCC}	0.9024	0.021842
Log. Likelihood	544.90	0.0396

The table presents coefficient estimates from a multivariate Dynamic Conditional Correlation Generalized Autoregressive Conditional Heteroskedasticity (DCC-GARCH) model for two sets of indices – ESG indices and Fintech indices. These estimates reflect the relationships between time varying volatilities and correlations among these indices returns focusing on their respective parameters α_{DCC}, β_{DCC}, and Log-Likelihood values.

The DCC-GARCH model estimates α_{DCC} at 0.06342 with a standard deviation of 0.01327 indicating that short-term volatility shocks have a moderate impact on the conditional correlation process. The β_{DCC}, value is 0.9024 with a standard deviation of 0.021842 showing that past conditional correlations have a strong influence on future correlations. The log likelihood value of 30.4755 with a standard deviation of 0.0803 suggests a reasonably good fit, indicating stable and consistent modelling of return dynamics for the NIFTY100 ESG Sector Leaders Index.

The BSE 100 ESG Index shows the same α_{DCC} and β_{DCC} values as the NIFTY100 ESG Sectors Leaders Index (0.05669) implying significant responsiveness to short term shocks in volatility, which could indicate higher volatility clustering. The β_{DCC} coefficient is 0.91595 (standard deviation 0.022248) showing a strong persistence in conditional correlations. The Log-Likelihood value of 44.123 (Standard deviation 0.0410) reflects moderate model fit quality suggesting reliable but somewhat less stable performance compared to the BSE 100 ESG Index.

These estimates indicate that Fintech indices, especially the S&P India Tech Index, exhibit higher short term volatility sensitivity compared to ESG indices. Meanwhile the BSE 100 ESG Index shows a stronger more stable long-term correlation structure with better model performance, as indicated by its higher Log-Likelihood value. These insights could help investors and analysts assess risk and correlation dynamics in these sectors, emphasizing the importance if persistence and volatility responsiveness in portfolio management decisions.

Granger Casualty Test

The following table summarizes the results from testing different lag lengths for Granger Causality analysis. The model with 1 lag is likely the best balance between complexity and fit according to the AIC, HQIC and SBIC, suggesting it should be used for our analysis. The next table outlines the results of Granger causality tests between pairs of variables in our study to identify if past values of one variable (first variable in the pair) can predict future values of another variable (second variable in the pair).

For seven variable pairs, the null hypothesis of no Granger causality is rejected (p-value < 0.05). This suggests that past values of the predictor variable have a statistically significant effect on forecasting the future values of the target variable. For example, past values of S&P 500 ESG Leaders significantly predict future values of MSCI World ESG Leaders, indicating a Granger causality from S&P 500 ESG Leaders to MSCI World ESG Leaders.

For the rest of the pairs, the null hypothesis cannot be rejected (p-value ≥ 0.05). This implies that there is insufficient statistical evidence to conclude that past values of the predictor variable have a significant effect on forecasting the future values of the target variable. In other words, for these pairs, one variable does not Granger-cause the other based on the data and significance level used.

Graph-2:

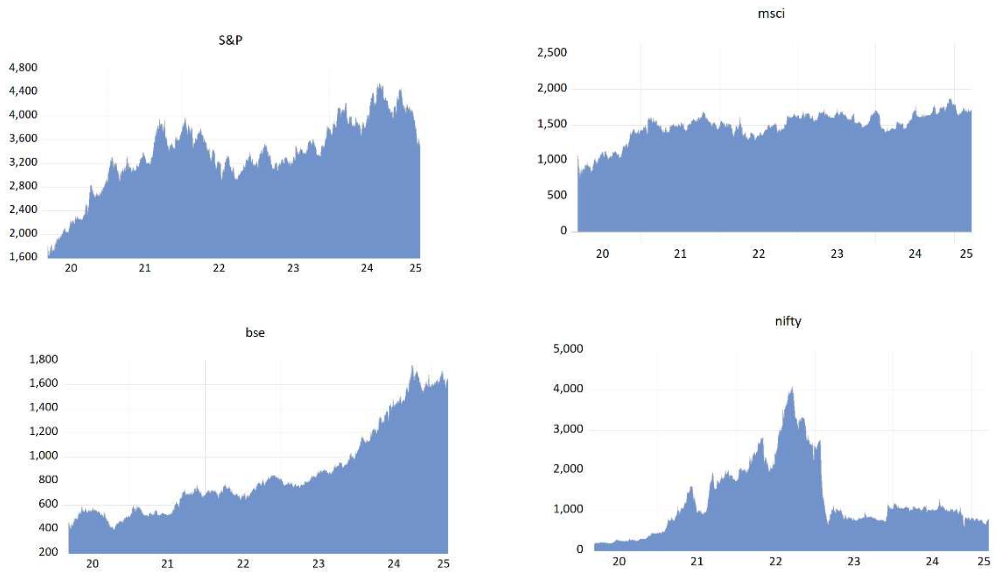


Table-2: Evaluation of optimal lag length

Lag	LL	LR	FPE	AIC	HQIC	SBIC
0	12677.16		1.73e -14	-20.33515	-20.32894	20.31863
1	12662.14	100.2797	1.64e -14	-20.39054	-20.30792	-20.35947
2	12677.40	30.29474	1.64e -14	-20.38395	-20.24062	-20.33341
3	12685.98	16.29447	1.66e -14	-20.37739	-20.16256	-20.29660

Volatility Spillover Results of Connectedness analysis

	S&P India Tech Index	**MSCI India Domestic Financials**	**NIFTY100 ESG Sector Leaders Index**	**BSE 100 ESG Index**	**FROM**
S&P India Tech Index	25.6	23.94	18.2	19.12	74.4
MSCI India Domestic Financials	22.72	13.48	18.49	19.08	73.77
NIFTY100 ESG Sector Leaders Index	13.79	32.56	14.89	23.18	67.44
BSE 100 ESG Index	15.83	18.03	22.82	26.35	73.65

TO	68.74	57.96	75.08	86.19	361.58
Inc. Own	94.34	90.52	102.76	112.54	
NET	-5.66	-9.48	2.76	12.54	
NPT	1	0	3	4	
cTCI/TCI					90.39/72.32

Granger Causality Results

Variable Pair	Coefficient	z	P>z	Results
S&P 500 India Tech Index → NIFTY 100 ESG Index	-0.31957	-1.26	0.1997	Do not Reject H_0
S&P 500 India Tech Index → BSE 100 ESG Index	0.145319	1.48	0.139	Do not Reject H_0
S&P 500 India Tech Index → MSCI India Domestic Financials	-0.22376	-1.44	0.151	Do not Reject H_0
NIFTY 100 ESG Index → S&P 500 India Tech Index	0.03973	-2.01	0.044	Reject Ho
MSCI India Domestic Financials → MSCI India Domestic Financials	-0.4283	0.55	0.579	Do not Reject Ho
MSCI India Domestic Financials → NIFTY 100 ESG Index	-0.61485	1.14	0.032	Reject Ho
MSCI India Domestic Financials → BSE 100 ESG Index	0.291885	1.95	0.043	Reject Ho
BSE 100 ESG Index → S&P 500 India Tech Index	0.400309	-0.78	0.433	Do not Reject Ho
BSE 100 ESG Index → NIFTY 100 ESG Index	-0.86538	1.3	0.194	Reject Ho
BSE 100 ESG Index → MSCI India Domestic Financials	-0.95337	-2.24	0.472	Do not Reject Ho

CONCLUSION

Given the remarkable increase in ESG investment as documented in the literature and overwhelming evidence on the implication of factors such as financial inclusion, green finance, energy efficiency etc for sustainable development a potential co-movement analysis between Fintech and ESG markets from a time series perspective has not been explored by scholars in the field. In this study we enhance the existing body of knowledge concerning the co-movement between Fintech and ESG markets. Our contribution involves investigating how their elements are interconnected within the time frequency domain. What sets our methodology apart is the examination of their correlation within the time frequency domain a novel approach that contrasts with traditional econometric techniques used to analyse market relationships.

Using daily data we perform wavelet coherence analysis. We find that the two Fintech indices are positively corelated with both ESG indices for a significantly large number of dates and frequencies. There also exists positive correlation between S&P India Tech India Index and both ESG Indices but to a lesser extent. In terms of the lead/lag relationship we find a bi-directional relationship between Fintech and ESG indices depending on dates and frequencies without one set of indices dominating the other.

For comparison and robustness, we also model multivariate dynamic constant correlation generalized autoregressive conditional heteroscedasticity models by taking a pair of indices at a time one from the Fintech indices and one from the ESG indices. We establish that all of the DCC GARCH processes are mean reverting. We also observe that the unconditional correlation from wavelet coherence and the DCC GARCH model for all the considered pairs. The average conditional correlations are greater for the DCC GARCH model than for the wavelet coherence model. Both of these conditional corelations are time-varying with the correlation based on the DCC-GARCH model being greater than the one based on wavelet coherence on average.

Last, wavelet coherence is such that it enables us to calculate average correlation over varying frequencies by time averaging of correlation. The nature of the correlation proves to be significant with the only exception of 256-day frequency, in lower frequencies i.e. 512-day (equivalent of roughly) two-year frequency correlation tends to be greater.

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