

Finance 5.0: Reimagining Financial Ecosystems in an Era of AI, Sustainability and Global Uncertainty: Green Finance as a Catalyst for Sustainable Financial Transformation

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Abstract

India's renewable-energy transition requires large and sustained capital mobilisation, yet India-specific empirical evidence linking green-finance flows to measurable renewable-energy outcomes remains limited. This study examines green-finance mobilisation, renewable-energy capacity, solar capacity, wind capacity and sovereign green-bond mobilisation in India over 2012–2026. The empirical design deliberately separates economy-wide green-finance flows from sovereign green bonds because the two series have different definitions and reporting histories. Renewable, solar and wind capacity are analysed for ten annual observations; comparable tracked green-finance data are available for only five years, and sovereign green bonds provide only four positive post-introduction observations. The analysis applies descriptive statistics, compound annual growth rates, correlations, linear and log-linear time-trend regressions, an exploratory green-finance–renewable-capacity regression, a measurement-sensitivity test and a log-log elasticity model. Renewable-energy capacity rises from 58,558 MW in 2017 to about 239,661 MW in 2026, with a CAGR of 16.95%. Solar capacity records the fastest expansion, with a CAGR of 32.83%, compared with 6.76% for wind. The log-linear renewable capacity trend explains 97.11% of the variation and implies annual growth of about 15%. In the five matched observations, green finance is positively associated with renewable capacity; the level coefficient is 0.12370 ($p=0.0036$), while the log-log elasticity is 0.3671 ($p=0.0076$). However, non-stationarity, missing and non-harmonised green-finance observations, the very small sample and the short sovereign-green-bond history prevent causal interpretation. The paper therefore contributes robust evidence on India's renewable-energy growth trajectory and preliminary evidence on the association between green finance and renewable capacity, while identifying priorities for improved green-finance data architecture and future econometric research.

Keywords: *green finance; renewable energy; solar energy; sovereign green bonds; India*

JEL Classification: *G20, H63, Q42, Q48, Q56*

Introduction

Climate finance has moved from a specialist area of environmental policy to a central component of economic and financial strategy. Countries seeking to decarbonise electricity systems must mobilise capital for renewable generation, transmission, storage, efficiency, clean transport and related infrastructure. Green finance provides a broad financial architecture for directing public and private capital towards such environmentally beneficial activities. In India, the issue is especially significant because renewable energy capacity has expanded rapidly, while the financing requirement to meet climate and development objectives remains exceptionally large.

The Indian experience offers a useful setting for examining whether the expansion of green finance is statistically associated with observable renewable-energy outcomes. The period 2017–2026 captures a phase of rapid renewable deployment, especially solar power, as well as the emergence of a more explicit green-finance policy architecture. Tracked economy-wide green-finance flows increased sharply in the earlier part of the period, while the Government of India introduced sovereign green bonds from FY2022–23. At the same time, the data environment remains imperfect: annual green-finance totals are not available on a fully harmonised basis for every year, definitions and coverage vary, and the sovereign-green-bond series is still too short for conventional time-series inference.

These characteristics create both an empirical opportunity and a methodological problem. A simple regression between green finance and renewable capacity may produce a strong positive relationship because both variables rise over time. Such a result can be economically suggestive but statistically misleading if trend and non-stationarity are ignored. Accordingly, this paper adopts a cautious design. It first establishes the underlying renewable-energy growth trajectory through level and log-linear time trends, then compares solar and wind expansion, and only thereafter examines the matched green-finance observations. Sovereign green bonds are treated separately because they represent a distinct instrument with a short post-introduction history.

The paper contributes to the literature in three ways. First, it provides an India-specific longitudinal assessment of renewable energy capacity, including solar and wind, over 2017–2026. Second, it links available green-finance flows to a concrete real-economy outcome—installed renewable capacity—rather than only to broad ESG or sustainability indicators. Third, it explicitly distinguishes robust trend evidence from preliminary association evidence, thereby avoiding claims that the available data cannot support. This distinction is important for both academic interpretation and policy design.

Choice of the Study

Green finance is frequently discussed as a catalyst for sustainable transformation, but the practical policy question is whether mobilisation of green capital is accompanied by measurable expansion in green productive assets. Renewable-energy capacity is a transparent and policy-relevant outcome because it reflects physical investment already connected to the energy transition. India also provides a compelling case because of the scale of its energy demand, its policy commitment to non-fossil capacity and the rapid shift in the composition of renewable generation.

The study is also chosen because the Indian evidence exposes a broader research problem: financial data and physical climate-transition data are often produced by different institutions using different definitions and reporting cycles. Economy-wide green-finance flows, sovereign green bonds and installed renewable capacity therefore cannot be treated as if they were one homogeneous annual series. A research design that recognises these differences can contribute not only substantive findings but also a methodological template for analysing emerging-market green finance.

Problem Statement

India has experienced rapid growth in renewable-energy capacity alongside increasing policy and regulatory attention to green finance, sovereign green bonds and sustainable investment. However, India-specific econometric evidence on the statistical relationship between green-finance mobilisation and renewable-energy development remains limited. The available data are incomplete and not fully harmonised across years; sovereign green bonds have been issued only since FY2022–23; and both green-finance flows and renewable-energy capacity exhibit strong upward trends. Consequently, it remains uncertain whether renewable-energy expansion can be statistically linked to green-finance mobilisation, whether solar and wind follow materially different growth paths, and whether the present sovereign-green-bond series is long enough for reliable inference. This study addresses these questions while separating statistically strong trend evidence from preliminary association evidence.

Objectives of the Study

- To examine the growth pattern of India's total renewable-energy capacity during 2017–2026.
- To test whether total renewable, solar and wind capacities exhibit statistically significant positive time trends.
- To compare the growth trajectories of solar and wind capacity and identify the principal contributor to renewable-energy expansion.
- To analyse the statistical relationship between tracked green-finance flows and renewable-energy capacity using matched observations.
- To estimate the responsiveness of renewable-energy capacity to changes in green-finance mobilisation through a log-log elasticity model.
- To test the sensitivity of the green-finance relationship to the alternative 2022 measurement based on mitigation finance only.
- To descriptively examine sovereign-green-bond mobilisation and assess whether the available post-introduction observations are sufficient for reliable econometric inference.
- To identify the data, measurement and econometric limitations that constrain causal interpretation and to propose directions for future research.

Coverage of the Time Period

The study covers 2012–2026. Renewable-energy, solar and wind capacity observations are available for all ten years. Comparable economy-wide green-finance observations are available only for 2017, 2018, 2019, 2020 and 2022, while sovereign green bonds have four positive annual observations from FY2022–23 onward. The 2026 renewable-capacity figure represents the latest available 2026 position rather than a completed FY2026–27 value. Missing green-finance observations are not interpolated.

Literature Review

Early work on green finance emphasised its role in reconciling financial development with environmental objectives. Mohammad and Kaushal (2018) evaluated the introduction of green finance and its probable impact on sustainable development in India. Their work was primarily conceptual and literature-based, leaving scope for country-specific empirical testing using measurable environmental or energy outcomes.

A recurring challenge in the literature is measurement. Bergedieck, Maheshwari and Avendano Ugaz (2016) proposed a bottom-up approach to tracking green-finance flows, noting that divergent definitions, classifications and data structures impede consistent aggregation across financial

institutions, projects and countries. This measurement problem is directly relevant to India, where annual green-finance observations are not available as one continuous, fully harmonised series.

Empirical research outside India generally finds that green finance can support environmental or sustainability outcomes, but the choice of dependent variable and institutional setting varies substantially. In 26 Asian economies, climate mitigation finance is connected with a decreased ecological footprint (Khan, Riaz, Ahmed and Saeed, 2022). Chen et al. (2023) found that the green total factor productivity of 28 Chinese provinces is positively affected by green finance, financial development and green technological innovation. Using panel data of 103 countries, Zheng, Wu, Feng and Chang (2025) found that green finance improved the countries' ESG performance and the effects were more pronounced in countries with better financial development, institutional quality and ICT development.

The recent literature also extends the idea of green finance beyond aggregate capital volumes. Transparency and the architecture of disclosure are fundamental for the functioning of green financial markets (Steuer and Tröger, 2022). Yu, Zhang and Lin (2026) claim that the spatial agglomeration of green finance in China may affect the flow of green-innovation factors and that there are nonlinearities. In the broader Industry 5.0 and digital transformation discourse, Bhandari, Paudel and Paudel (2026) position green-finance instruments, noting the increasing convergence of finance, ESG, green innovation and technology-enabled sustainability systems

Books and integrative works further underline the multidimensional nature of the field. Köhn (2012) links environmental finance to the financing of renewable energy and energy efficiency in developing and transition economies. J. Dziwok and T. Jäger (2024). A critical review of mainstream green finance and counter-views. – Baber and Fanea-Ivanovici (2025) Green finance, crowdfunding and digital currencies. Wang et al. (2019) connect internet finance, green finance and sustainability. These contributions widen the conceptual field but do not resolve the specific empirical question of whether observed green-finance mobilisation in India moves together with a physical renewable-energy outcome.

Taken together, prior studies support the proposition that green finance can matter for sustainability, environmental performance, innovation and green productivity. Yet they also reveal heterogeneity in measurement, instruments, countries and outcomes. Much of the empirical evidence is cross-country or China-centred; India-specific work remains comparatively limited, and sovereign green bonds have only recently become observable as a separate financing instrument.

Table 1. Selected Literature and Relevance to the Present Study

Study	Setting/Focus	Main Insight	Gap Relevant Here
Bergedieck et al. (2016)	Green-finance tracking	Definitions and data heterogeneity constrain measurement	Supports caution on harmonisation
Mohammad & Kaushal (2018)	India; conceptual review	Green finance supports sustainable development	Limited empirical testing
Khan et al. (2022)	26 Asian economies	Climate-mitigation finance lowers ecological footprint	Broad Asia; not India-specific
Chen et al. (2023)	28 Chinese provinces	Green finance supports green productivity	China; aggregate green-finance index

Zheng et al. (2025)	103 countries	Green finance improves national ESG performance	Broad ESG outcome rather than RE capacity
Yu et al. (2026)	China	Nonlinear effects on green-innovation-factor flows	Spatial innovation focus
Bhandari et al. (2026)	Bibliometric/Industry 5.0	Green finance increasingly integrated with digital sustainability	No India-specific RE econometrics

Research Gap

Geographical gap: there is limited India-specific econometric evidence connecting green-finance mobilisation with measurable renewable-energy outcomes.

Outcome-measurement gap: prior studies commonly use ESG scores, ecological footprint or green productivity rather than installed renewable, solar and wind capacity.

Instrument-specific gap: aggregate green finance and sovereign green bonds are often not separated, even though they have different economic meanings and reporting histories.

Time-trend gap: few studies explicitly distinguish the effect of a common upward trend from a possible finance–capacity relationship; trending levels can generate spurious regression.

Technology-specific gap: solar and wind have markedly different growth paths, but this heterogeneity is often hidden inside aggregate renewable indicators.

Data and econometric gap: incomplete annual green-finance observations, short time series, non-stationarity and limited controls restrict the use of advanced causal models.

Sovereign-green-bond gap: India’s short post-2022 issuance history is insufficient for reliable econometric evaluation of the instrument’s independent contribution.

Accordingly, the present study addresses the gap by estimating total and technology-specific capacity trends, examining the matched green finance–renewable capacity relationship, calculating a descriptive elasticity, conducting measurement-sensitivity analysis and evaluating the present adequacy of sovereign-green-bond data. The intended contribution is robust evidence on renewable-energy trends and preliminary evidence on financial association—not definitive evidence of causality.

Hypotheses

H01: Green-finance mobilisation has no statistically significant positive relationship with renewable-energy capacity in India.

H11: Green-finance mobilisation has a positive and statistically significant relationship with renewable-energy capacity in India.

H02: A percentage increase in green finance is not associated with a statistically significant positive percentage increase in renewable-energy capacity.

H12: A percentage increase in green finance is associated with a positive and statistically significant percentage increase in renewable-energy capacity.

H03a: Total renewable capacity does not exhibit a statistically significant positive time trend.

H13a: Total renewable capacity exhibits a positive and statistically significant time trend.

H03b: Solar capacity does not exhibit a statistically significant positive time trend.

H13b: Solar capacity exhibits a positive and statistically significant time trend.

H03c: Wind capacity does not exhibit a statistically significant positive time trend.

H13c: Wind capacity exhibits a positive and statistically significant time trend.

H04: Sovereign-green-bond mobilisation has no statistically significant positive relationship with renewable-energy development in India.

H14: Sovereign-green-bond mobilisation has a positive and statistically significant relationship with renewable-energy development in India.

Database and Methodology

The database combines five series from the supplied research-ready dataset: tracked green-finance flows (GF, ₹ crore), sovereign green-bond mobilisation (SGB, ₹ crore), aggregate renewable-energy capacity excluding large hydro (REC, MW), solar capacity (SOLAR, MW) and wind capacity (WIND, MW). The principal source families identified in the dataset are Climate Policy Initiative for economy-wide green-finance flows, the Department of Economic Affairs for sovereign green bonds, and the Ministry of New and Renewable Energy for renewable-capacity indicators. The analysis preserves these variables separately because their definitions, timing conventions and reporting coverage differ.

Renewable, solar and wind series contain ten annual observations. Green finance contains five matched observations: 2017, 2018, 2019, 2020 and 2022. For 2022, the baseline GF observation is ₹480,400 crore, the arithmetic combination of ₹371,200 crore mitigation finance and ₹109,200 crore adaptation finance. Because the combined figure may not be directly comparable with earlier observations, a sensitivity regression uses ₹371,200 crore of mitigation finance only. Sovereign green bonds have four positive observations, from 2023 to 2026 in the annualised dataset.

The empirical procedure begins with descriptive statistics and compound annual growth rates. Pearson correlations are reported for REC, SOLAR and WIND, but these variables are not entered together in a regression for REC because solar and wind are components of aggregate renewable capacity; simultaneous inclusion would create severe multicollinearity and partly restate an accounting identity. Time-trend regressions are therefore estimated separately for each capacity series.

$$REC_t = \alpha + \beta \text{TREND}_t + \varepsilon_t$$

where TREND = 1 for 2017, 2 for 2018, ..., 10 for 2026. A log-linear model is also estimated:

$$\ln(REC_t) = \alpha + \beta \text{TREND}_t + \varepsilon_t$$

In the log-linear trend model, the exact annual growth rate is calculated as $[\exp(\beta) - 1] \times 100$. Technology-specific versions of the same model are estimated for SOLAR and WIND.

The matched green-finance relationship is examined using a parsimonious exploratory regression:

$$REC_t = \beta_0 + \beta_1 GF_t + \varepsilon_t$$

A log-log specification measures descriptive elasticity:

$$\ln(REC_t) = \beta_0 + \beta_1 \ln(GF_t) + \varepsilon_t$$

In the log-log specification, β_1 is interpreted as the percentage change in renewable-energy capacity associated with a 1% change in measured green finance. Diagnostic evidence is interpreted cautiously because the annual samples are very small. The log-REC trend model is examined using Jarque–Bera normality, Breusch–Pagan heteroskedasticity, Breusch–Godfrey serial correlation, Durbin–Watson and Augmented Dickey–Fuller diagnostics. Statistical significance does not override the data limitations: the GF regressions are explicitly treated as exploratory associations, not structural causal estimates.

Table 2. Dataset Used in the Empirical Analysis

Year	GF (₹ cr.)	SGB (₹ cr.)	REC (MW)	Solar (MW)	Wind (MW)
2017	111,000	0	58,558.19	12,782.52	32,279.77
2018	137,000	0	70,651.43	22,346.21	34,145.00
2019	266,000	0	79,411.99	29,097.18	35,625.97
2020	352,000	0	88,255.30	35,607.24	37,743.76
2021	NA	0	95,803.41	41,236.04	39,247.06
2022	480,400	0	109,885.38	53,996.54	40,357.59
2023	NA	16,000	125,159.81	66,780.34	42,633.14
2024	NA	20,000	143,644.49	81,813.58	45,886.52
2025	NA	21,697.4	172,368.14	105,646.45	50,037.83
2026	NA	15,000	239,661.00	164,594.75	58,136.89

Data Interpretation and Empirical Results

Descriptive Growth Pattern

Aggregate renewable-energy capacity increased from 58,558.19 MW in 2017 to approximately 239,661 MW in 2026, a more than fourfold increase. The corresponding CAGR is 16.95%. The technology composition is even more revealing. Solar capacity increased from 12,782.52 MW to 164,594.75 MW, producing a CAGR of 32.83%, while wind increased from 32,279.77 MW to 58,136.89 MW, a CAGR of 6.76%. Solar therefore emerges as the dominant source of acceleration in the aggregate series.

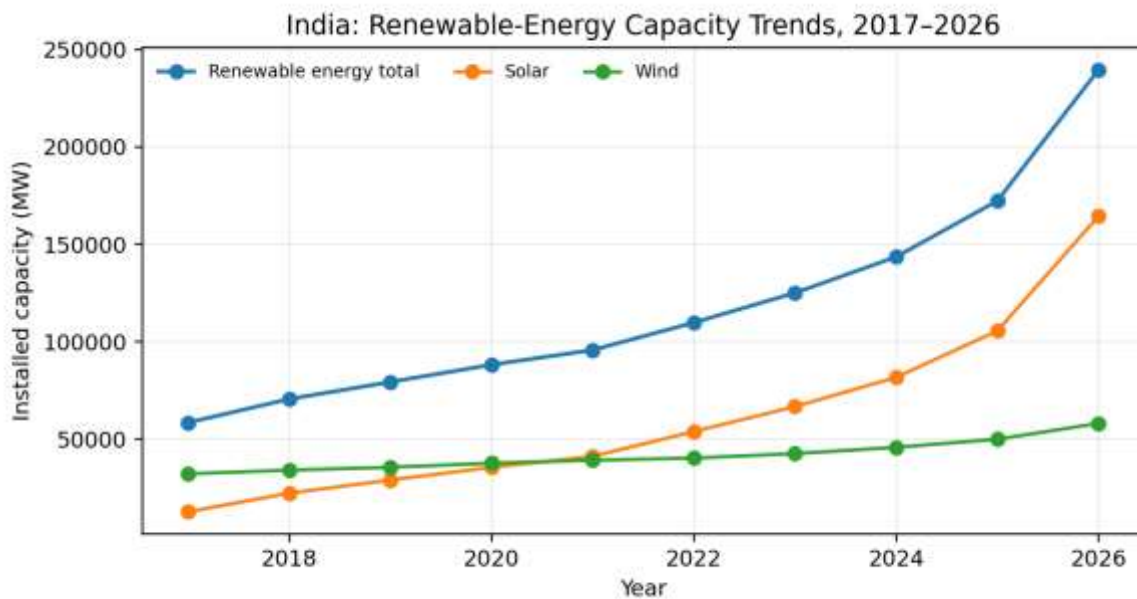


Figure 1. India's renewable, solar and wind installed capacity, 2017–2026.

The very high correlations among REC, SOLAR and WIND—0.9998 between REC and solar, 0.9967 between REC and wind, and 0.9947 between solar and wind—are expected because the component technologies jointly shape aggregate renewable capacity. These correlations describe co-movement rather than independent causal relationships.

Time-Trend Regression

The regression of aggregate renewable capacity with linear trend yields the annual coefficient of 16,896.37 MW ($t=7.215$, $p=0.00009$), $R^2=0.8668$. Thus, the estimated average annual increase over

the sample is nearly 16.9 GW. The low Durbin–Watson statistic of 0.942 indicates positive residual persistence and suggests that a simple linear trend does not fully capture the accelerating pattern.

The log-linear model fits the data substantially better. The estimated trend coefficient is 0.1398 ($t=16.389$, $p<0.001$), with $R^2=0.971$ and adjusted $R^2=0.9675$. Transforming the coefficient gives an exact annual growth rate of about 15.0%. The technology-specific log models confirm significant positive trends for all three series at $p<0.001$. Solar has the largest log-trend coefficient (0.2497) and a log-model R^2 of 0.980, while wind has a coefficient of 0.0584 and R^2 of 0.952. These results strongly reject the null hypotheses of no positive time trend for REC, solar and wind.

Table 3. Trend and Growth Results

Series	Annual level increase	Level R^2	Log-trend coefficient i.e. β	Log Model R^2	CAGR
Renewable capacity	16,896 MW	0.867	0.1398	0.971	16.95%
Solar capacity	14,056 MW	0.853	0.2497	0.980	32.83%
Wind capacity	2,491 MW	0.907	0.0584	0.952	6.76%

Green Finance and Renewable Capacity

The baseline exploratory model is estimated as $REC = 48,042.90 + 0.12370 \text{ GF}$. The GF coefficient is positive and statistically significant ($t=8.363$, $p=0.0036$), and the model R^2 is 0.9589. In numerical terms, an additional ₹10,000 crore of measured green finance is associated with approximately 1,237 MW of additional renewable capacity in the matched observations. The GF–REC correlation is approximately 0.979.

The association is economically plausible but cannot be interpreted causally. Both series increase over time, the number of observations is only five, and the GF measure is not fully harmonised across years. The high R^2 therefore reflects both genuine co-movement and the common growth trend. The result should be read as evidence that green-finance mobilisation and renewable deployment moved together during the observed years, not as a quantified causal effect of finance on capacity.

Measurement Sensitivity and Elasticity

When the 2022 observation is changed from the combined ₹480,400 crore measure to mitigation finance of ₹371,200 crore, the estimated GF coefficient rises to 0.14822 ($t=3.983$, $p=0.0283$), while R^2 falls to 0.8410. The positive sign remains significant at the 5% level, but the magnitude and fit are materially affected by the measurement choice. This confirms that comparability of green-finance definitions is not a minor technical issue; it directly influences empirical estimates.

The log-log specification yields an elasticity coefficient of 0.3671 ($t=6.430$, $p=0.0076$; $R^2=0.9323$). Thus, within the five matched observations, a 1% increase in measured green finance is associated with approximately a 0.37% increase in renewable-energy capacity. Because both variables are trending and $N=5$, the coefficient is best described as a descriptive elasticity rather than a structural parameter.

Sovereign Green Bonds

India’s sovereign green-bond programme is an important policy innovation, but the available data do not yet support a reliable econometric conclusion. Cumulative mobilisation over FY2022–23 to FY2025–26 is ₹72,697.40 crore in the supplied dataset. A regression using the four positive annual observations produces an SGB coefficient of -5.3489 ($t=-0.511$, $p=0.660$; $R^2=0.1156$). No substantive interpretation should be attached to the negative sign. Annual bond mobilisation fluctuates, whereas REC is a cumulative stock that rises over time, and four observations are inadequate for meaningful

inference. The appropriate conclusion is that the current evidence is insufficient to reject the null hypothesis; it is not evidence that sovereign green bonds reduce renewable capacity.

Diagnostic Tests and Econometric Cautions

Diagnostic	Result	Interpretation
Jarque–Bera normality	JB=1.993; p=0.369	No evidence against residual normality
Breusch–Pagan	LM p=0.066; F p=0.078	Borderline, not significant at 5%
Breusch–Godfrey LM, lag 1	LM p=0.068; F p=0.104	Possible residual persistence; not significant at 5%
Durbin–Watson	0.942	Suggests positive serial dependence
ADF on ln (REC), trend	ADF=1.715; p≈1.000	Cannot reject non-stationarity

The diagnostics reinforce the central caution of the paper. With only ten annual observations, asymptotic test properties are weak. The inability to reject non-stationarity in ln(REC) and the evidence of residual persistence mean that regressions between trending levels can be spurious. The strongest econometric conclusion is therefore the existence of a rapid and statistically significant renewable-energy trend; the finance regressions remain exploratory.

Consolidated Hypothesis Decisions

Hypothesis	Decision	Reason
H01/H11: GF–REC level	Reject H01 in matched sample	Positive coefficient, p=0.0036; exploratory only
H02/H12: GF elasticity	Reject H02 in matched sample	Elasticity 0.3671, p=0.0076; descriptive
H03a/H13a: REC trend	Reject H03a	Positive trend, p<0.001
H03b/H13b: Solar trend	Reject H03b	Positive trend, p<0.001
H03c/H13c: Wind trend	Reject H03c	Positive trend, p<0.001
H04/H14: SGB–REC	Insufficient evidence to reject H04	Only four positive observations; p=0.660

Discussion

The empirical results portray India’s renewable-energy transition as a strongly accelerating physical transformation led by solar deployment. The difference between solar and wind is sufficiently large to matter for finance and policy. A financing strategy based only on aggregate renewable capacity may obscure technology-specific investment requirements, risk profiles, project structures and infrastructure bottlenecks. Solar’s rapid expansion may reflect modularity, declining technology costs, utility-scale procurement and distributed applications, while wind expansion follows a different project and site profile. The present data do not identify these mechanisms directly, but the divergence in growth rates is clear.

The positive GF–REC association is consistent with the broad literature linking green finance with improved environmental, ESG or green-productivity outcomes. However, this study adds a specific caution: association is not enough when both finance and capacity trend upward. The empirical challenge is therefore not simply to obtain a significant coefficient, but to show that the coefficient survives better identification, longer and more harmonised data, controls for macroeconomic and sectoral conditions, and models that address non-stationarity.

The sovereign-green-bond findings illustrate another important principle. A new financial instrument can be institutionally important before it is econometrically measurable. India's framework creates a labelled sovereign channel for financing eligible green public expenditures, but four positive annual observations cannot identify its independent effect on an accumulated physical stock. Evaluation should instead develop through allocation and impact reporting, project-level use-of-proceeds information and, over time, a longer quarterly or annual dataset that permits stronger inference.

From a financial-system perspective, the results support the need to treat data architecture as part of green-finance policy. Without consistent definitions and continuous time-series reporting, policymakers may be able to mobilise capital but remain unable to evaluate its incremental impact rigorously. Harmonised reporting would improve accountability, allow instrument-level comparison and support more sophisticated models of how public and private finance translate into renewable investment.

Summary

The research is based on a research-ready annual dataset to analyse green finance and renewable-energy development in India for the period 2017–2026. Aggregate renewable capacity expanded rapidly, with a CAGR of 16.95%, while solar grew at 32.83% and wind at 6.76%. Time-trend models are strongly significant, and the log-linear REC model explains 97.11% of the variation while implying annual growth of about 15%. In the five years with matched green-finance observations, GF is positively associated with REC and the log-log elasticity is 0.3671. A sensitivity test confirms the positive sign but shows that results vary with the 2022 measurement choice. Sovereign green bonds have only four positive annual observations and cannot yet be evaluated reliably through regression. The evidence is therefore strongest on the renewable-energy growth trajectory and preliminary on the finance–capacity association.

Conclusion

India's renewable-energy expansion over 2017–2026 is statistically strong, economically large and increasingly solar-led. The physical scale of the transition is evident from the rise in aggregate capacity from about 58.6 GW to almost 239.7 GW in the dataset. The econometric trend evidence is robust within the limits of the short sample, and the log-linear model provides a particularly good description of the accelerating growth path.

Green-finance mobilisation is positively associated with renewable capacity in the limited matched observations. This finding is consistent with the proposition that financial mobilisation and physical transition can reinforce one another, but the present dataset cannot establish the direction of causality. The strong common trend, non-stationarity, missing observations and measurement discontinuities require restraint. Similarly, the sovereign-green-bond programme is too recent for a credible independent-effects regression.

The central conclusion is therefore twofold: India has achieved rapid renewable-energy scale-up, especially in solar, and available green-finance data move positively with that expansion; however, the next stage of research must shift from documenting co-movement to identifying mechanisms and causal effects. Achieving that objective depends as much on better data design as on more sophisticated econometric techniques.

Recommendations

Create a harmonised annual green-finance series. A common classification covering sources, instruments, sectors and end uses should be maintained consistently over time so that year-to-year changes can be interpreted economically.

Publish instrument-level and project-level linkages. Green bonds, loans, budgetary support, blended finance and other instruments should be separately identifiable and linked, where feasible, to funded renewable or adaptation outcomes.

Expand the sovereign-green-bond evidence base. Quarterly issuance, allocation and impact information should be compiled in a machine-readable longitudinal dataset to permit evaluation once a sufficiently long history becomes available.

Use higher-frequency or panel data. Quarterly national data or state-level/project-level panels would increase observations and enable fixed effects, dynamic models and stronger identification strategies.

Control explicitly for macroeconomic and energy-sector factors. Future models should incorporate GDP growth, renewable-energy FDI, electricity demand, policy changes, technology costs, interest rates, exchange rates and other relevant determinants where consistent data are available.

Apply time-series methods once data permit. Unit-root and cointegration testing, ARDL/error-correction models, structural-break tests and robust standard errors should be used when sample length becomes adequate.

Maintain technology-specific analysis. Solar, wind and other renewable technologies should not be treated as homogeneous because financing structures, risks and deployment patterns differ substantially.

Link financial mobilisation to impact reporting. Policy evaluation should progress from measuring capital raised to measuring additional capacity, emissions avoided, energy generated and other environmental outcomes attributable to funded projects.

Limitations and Scope for Future Research

The most important limitation is sample size. GF has five comparable observations and SGB only four positive observations, while the renewable-capacity series contains ten annual observations. The green-finance figures are also not fully harmonised across years, and the 2022 observation requires an explicit measurement choice. The 2026 capacity observation is a latest-available position rather than a completed financial-year value. The analysis does not include a full set of macroeconomic, policy, technology-cost or foreign-investment controls. Future research should therefore construct a longer and more granular dataset, distinguish financial instruments, use panel or quarterly designs, and test whether the finance–renewable relationship persists after controlling for common trends, structural breaks and endogeneity.

Appendix

(A) Econometric Analysis

Econometric Objective and Research Questions

The empirical objective is to examine the statistical relationship between green-finance mobilisation and renewable-energy development in India, while recognising the limitations of a short annual time series. The analysis also tests whether renewable, solar and wind capacity exhibit statistically significant upward trends over the period.

The analysis addresses three questions: (i) whether renewable-energy capacity has increased significantly over time; (ii) whether observed green-finance flows are positively associated with renewable-energy capacity; and (iii) whether the post-2022 sovereign green bond series is presently long enough to support reliable econometric inference.

Variables and Data Structure

Variable	Symbol	Measurement	Available observations
Tracked Green Finance	GF	₹ crore	5 (2017, 2018, 2019, 2020, 2022)
Sovereign Green Bonds	SGB	₹ crore	10 overall; 4 positive observations
Renewable-Energy Capacity	REC	MW	10
Solar Capacity	SOLAR	MW	10
Wind Capacity	WIND	MW	10
Time Trend	TREND	1 to 10	10

For 2022, the source reports ₹371,200 crore of mitigation finance and ₹109,200 crore of adaptation finance, giving an arithmetic combined amount of ₹480,400 crore. Because the source cautions that the combined figure may differ in scope and methodology from earlier observations, the main exploratory regression uses ₹480,400 crore, and a sensitivity regression uses ₹371,200 crore.

Descriptive Statistics

Variable	N	Mean	Std. Dev.	Minimum	Maximum
Green Finance (₹ crore)	5	269,280.00	153,277.17	111,000.00	480,400.00
Sovereign Green Bonds (₹ crore)	10	7,269.74	9,564.32	0.00	21,697.40
Renewable Capacity (MW)	10	118,339.91	54,947.02	58,558.19	239,661.00
Solar Capacity (MW)	10	61,390.09	46,081.52	12,782.52	164,594.75
Wind Capacity (MW)	10	41,609.35	7,917.56	32,279.77	58,136.89

Renewable-energy capacity increased from 58,558.19 MW in 2017 to approximately 239,661 MW in 2026. The corresponding compound annual growth rate (CAGR) is approximately 16.95%. Solar capacity increased at approximately 32.83% per year, compared with about 6.76% for wind capacity. The descriptive evidence therefore indicates that solar power was the principal source of acceleration in the renewable-capacity series.

Correlation Analysis

Variable	REC	SOLAR	WIND
REC	1.0000	0.9998	0.9967
SOLAR	0.9998	1.0000	0.9947
WIND	0.9967	0.9947	1.0000

The correlations among REC, SOLAR and WIND are extremely high because solar and wind are major components of aggregate renewable capacity. Consequently, using SOLAR and WIND simultaneously as explanatory variables for REC would create severe multicollinearity and would partly reproduce an accounting identity rather than identify an independent behavioural relationship.

Time-Trend Regression Results

A parsimonious trend model is estimated first:

$$REC_t = \alpha + \beta \text{TREND}_t + \varepsilon_t$$

where TREND = 1 for 2017, 2 for 2018, ..., 10 for 2026.

$$REC_t = 25,409.91 + 16,896.37 \text{TREND}_t$$

Statistic	Estimate
Trend coefficient	16,896.37 MW
t-statistic	7.215
p-value	0.00009
R ²	0.8668
Adjusted R ²	0.8501
F-statistic	52.052
Prob(F)	0.00009
Durbin-Watson	0.811

The linear trend coefficient is positive and highly significant. On average, renewable-energy capacity increased by about 16,896 MW per year. The model explains approximately 86.7% of the variation in REC. The low Durbin-Watson statistic, however, indicates positive residual persistence and suggests that a simple linear trend does not fully capture the accelerating growth pattern.

Log-Linear Growth Model

$$\ln(REC_t) = \alpha + \beta \text{TREND}_t + \varepsilon_t$$

$$\ln(REC_t) = 10.8256 + 0.13985 \text{TREND}_t$$

Statistic	Estimate
Trend coefficient	0.13985
t-statistic	16.389
p-value	< 0.001
R ²	0.9711
Adjusted R ²	0.9675
Durbin-Watson	0.942

The log-linear specification provides a substantially better fit. The exact annual growth rate implied by the trend coefficient is $[\exp(0.13985) - 1] \times 100 \approx 15.0\%$. Thus, the model indicates that renewable-energy capacity expanded at roughly 15% per year over the sample period.

Technology-Specific Trend Models

Dependent variable	Annual level increase	Level R ²	Log-trend coefficient i.e. β	Log-model R ²
Renewable capacity	16,896 MW	0.867	0.1398	0.971
Solar capacity	14,056 MW	0.853	0.2497	0.980
Wind capacity	2,491 MW	0.907	0.0584	0.952

All three time-trend coefficients are statistically significant at $p < 0.001$. Solar capacity displays the fastest proportional expansion, with a log-trend coefficient of approximately 0.2497, compared with 0.0584 for wind. This supports rejection of H03 in favour of H13.

6. Exploratory Green Finance–Renewable Capacity Regression

Because green-finance values are available for only five years, the following model is treated as exploratory:

$$REC_t = \beta_0 + \beta_1 GF_t + \varepsilon_t$$

$$REC_t = 48,042.90 + 0.12370 GF_t$$

Statistic	Estimate
GF coefficient	0.12370
t-statistic	8.363
p-value	0.0036
R ²	0.9589
Adjusted R ²	0.9452
F-statistic	69.939
Observations	5
Durbin-Watson	2.705

The coefficient is positive and statistically significant in the five-observation sample. Numerically, an additional ₹10,000 crore of measured green finance is associated with approximately 1,237 MW of additional renewable-energy capacity. The correlation between GF and REC in these observations is approximately 0.979. This result shows association only: both series rise over time, the sample is extremely small, and the green-finance observations are not fully harmonised.

Sensitivity Test: 2022 Mitigation Finance Only

$$REC_t = 44,676.75 + 0.14822 GF_t$$

Statistic	Estimate
GF coefficient	0.14822
t-statistic	3.983
p-value	0.0283
R ²	0.8410
Adjusted R ²	0.7880
Observations	5

When the 2022 observation is restricted to ₹371,200 crore of mitigation finance rather than the ₹480,400 crore combined figure, the positive coefficient remains statistically significant at the 5% level. However, model fit falls from $R^2 = 0.959$ to $R^2 = 0.841$. This sensitivity confirms that the result depends materially on measurement choices and should not be overstated.

Log-Log Elasticity Model

$$\ln(\text{REC}_t) = \alpha + \beta \ln(\text{GF}_t) + \varepsilon_t$$

$$\ln(\text{REC}_t) = 6.7473 + 0.3671 \ln(\text{GF}_t)$$

Statistic	Estimate
Elasticity coefficient	0.3671
t-statistic	6.430
p-value	0.0076
R ²	0.9323
Observations	5

The estimated elasticity suggests that a 1% increase in measured green finance is associated with approximately a 0.37% increase in renewable-energy capacity in the available observations. Again, because N = 5 and both variables trend upward, this should be presented as a descriptive elasticity rather than a causal structural estimate.

Sovereign Green Bond Regression

Sovereign Green Bonds were introduced only in FY2022–23, leaving four positive annual observations. A post-introduction exploratory regression produces a negative but statistically insignificant coefficient:

$$\text{REC}_t = 267,420.25 - 5.3489 \text{ SGB}_t$$

Statistic	Estimate
SGB coefficient	-5.3489
t-statistic	-0.511
p-value	0.660
R ²	0.1156
Adjusted R ²	-0.3267
Observations	4

No substantive economic conclusion should be drawn from this coefficient. The negative sign does not imply that green bonds reduce renewable capacity; it reflects a four-observation sample in which annual bond mobilisation fluctuates while REC is a cumulative stock variable. H02 therefore cannot be meaningfully tested with the current post-introduction sample.

Diagnostic Tests and Econometric Cautions

Diagnostic	Log-REC trend model	Interpretation
Jarque–Bera normality test	JB = 1.993; p = 0.369	No evidence against residual normality
Breusch–Pagan heteroskedasticity test	LM p = 0.066; F p = 0.078	Borderline but not significant at 5%
Breusch–Godfrey LM, lag 1	LM p = 0.068; F p = 0.104	Possible residual persistence; not significant at 5%
Durbin–Watson	0.942	Suggests positive serial dependence
ADF test on ln (REC), trend included	ADF = 1.715; p ≈ 1.000	Cannot reject non-stationarity in this very short sample

The diagnostics should be interpreted cautiously because asymptotic test properties are weak with only 10 annual observations. The inability to reject a unit root reinforces the danger of spurious regression when two trending level variables are regressed on one another. For this reason, the time-trend models are used primarily to describe growth, and the GF–REC regressions are explicitly labelled exploratory.

Appendix A. Dataset Used in the Econometric Analysis

Year	GF (₹ crore)	SGB (₹ crore)	REC (MW)	Solar (MW)	Wind (MW)
2017	111,000	0	58,558.19	12,782.52	32,279.77
2018	137,000	0	70,651.43	22,346.21	34,145.00
2019	≈266,000	0	79,411.99	29,097.18	35,625.97
2020	≈352,000	0	88,255.30	35,607.24	37,743.76
2021	NA	0	95,803.41	41,236.04	39,247.06
2022	480,400*	0	109,885.38	53,996.54	40,357.59
2023	NA	16,000	125,159.81	66,780.34	42,633.14
2024	NA	20,000	143,644.49	81,813.58	45,886.52
2025	NA	21,697.40	172,368.14	105,646.45	50,037.83
2026	NA	15,000	≈239,661	164,594.75	58,136.89

*2022 GF = ₹371,200 crore mitigation finance + ₹109,200 crore adaptation finance = ₹480,400 crore combined. A separate sensitivity regression uses mitigation finance only. The 2026 renewable capacity observation is the latest available 2026 observation rather than a completed FY2026–27 value.

(B) Calculation Appendix

Dataset Used for the Calculations

Year	GF (₹ crore)	SGB (₹ crore)	REC (MW)	Solar (MW)	Wind (MW)
2017	111,000	0	58,558.19	12,782.52	32,279.77
2018	137,000	0	70,651.43	22,346.21	34,145.00
2019	≈266,000	0	79,411.99	29,097.18	35,625.97
2020	≈352,000	0	88,255.30	35,607.24	37,743.76
2021	NA	0	95,803.41	41,236.04	39,247.06
2022	480,400*	0	109,885.38	53,996.54	40,357.59
2023	NA	16,000	125,159.81	66,780.34	42,633.14
2024	NA	20,000	143,644.49	81,813.58	45,886.52
2025	NA	21,697.40	172,368.14	105,646.45	50,037.83
2026	NA	15,000	≈239,661.00	164,594.75	58,136.89

*For 2022, the baseline GF value is ₹480,400 crore = ₹371,200 crore mitigation finance + ₹109,200 crore adaptation finance. A separate sensitivity regression uses mitigation finance only (₹371,200 crore).

2. Descriptive Statistics: Green Finance

Available green-finance observations are ₹111,000 crore, ₹137,000 crore, ₹266,000 crore, ₹352,000 crore and ₹480,400 crore.

Number of observations:

N = 5

Sum:

$$\Sigma GF = 111,000 + 137,000 + 266,000 + 352,000 + 480,400$$

$$\Sigma GF = 1,346,400$$

$$\text{Mean GF} = \Sigma GF / N = 1,346,400 / 5 = ₹269,280 \text{ crore}$$

$$\text{Sample } s = \sqrt{[\Sigma (GF_i - \bar{GF})^2 / (N - 1)]} = ₹153,277.17 \text{ crore}$$

Statistic	Green Finance
N	5
Mean	₹269,280.00 crore
Std. Dev.	₹153,277.17 crore
Minimum	₹111,000.00 crore
Maximum	₹480,400.00 crore

Descriptive Statistics: Renewable-Energy Capacity

The ten REC observations are 58,558.19; 70,651.43; 79,411.99; 88,255.30; 95,803.41; 109,885.38; 125,159.81; 143,644.49; 172,368.14; and 239,661.00 MW.

Sum and mean:

$$\Sigma REC = 1,183,399.14 \text{ MW}$$

$$REC = 1,183,399.14 / 10 = 118,339.914 \text{ MW}$$

Sample standard deviation:

$$\Sigma (REC_i - REC)^2 = 27,172,574,115.73$$

$$sREC = \sqrt{(27,172,574,115.73 / 9)}$$

$$sREC = 54,947.02 \text{ MW}$$

Statistic	REC
N	10
Mean	118,339.91 MW
Std. Dev.	54,947.02 MW
Minimum	58,558.19 MW
Maximum	239,661.00 MW

Compound Annual Growth Rate (CAGR)

$$CAGR = [(Ending \text{ Value} / Beginning \text{ Value})^{(1/n)} - 1] \times 100$$

For 2017–2026, there are nine annual growth intervals ($n = 9$).

Renewable-energy capacity:

$$CAGR = [(239,661 / 58,558.19)^{(1/9)} - 1] \times 100$$

$$= (4.0934^{(1/9)} - 1) \times 100$$

$$= 16.95\%$$

Solar capacity:

$$CAGR = [(164,594.75 / 12,782.52)^{(1/9)} - 1] \times 100$$

$$= 32.83\%$$

Wind capacity:

$$CAGR = [(58,136.89 / 32,279.77)^{(1/9)} - 1] \times 100$$

$$= 6.76\%$$

Series	2017	2026	CAGR
REC	58,558.19	239,661.00	16.95%
Solar	12,782.52	164,594.75	32.83%
Wind	32,279.77	58,136.89	6.76%

Pearson Correlation Calculations

$$r_{XY} = \Sigma [(X_i - \bar{X}) (Y_i - \bar{Y})] / \sqrt{\{\Sigma (X_i - \bar{X})^2 \times \Sigma (Y_i - \bar{Y})^2\}}$$

REC and Solar:

$$\Sigma(\text{REC} - \text{REC}\bar{C}) (\text{Solar} - \text{Solar}\bar{C}) = 22,782,824,416.10$$

$$\Sigma(\text{REC} - \text{REC}\bar{C})^2 = 27,172,574,115.73$$

$$\Sigma(\text{Solar} - \text{Solar}\bar{C})^2 = 19,111,559,115.16$$

$$r = 22,782,824,416.10 / \sqrt{(27,172,574,115.73 \times 19,111,559,115.16)}$$

$$r = 0.999756 \approx 0.9998$$

REC and Wind:

$$\Sigma(\text{REC} - \text{REC}\bar{C}) (\text{Wind} - \text{Wind}\bar{C}) = 3,902,467,101.23$$

$$\Sigma(\text{Wind} - \text{Wind}\bar{C})^2 = 564,189,706.05$$

$$r = 0.996693 \approx 0.9967$$

Solar and Wind:

$$\Sigma(\text{Solar} - \text{Solar}\bar{C}) (\text{Wind} - \text{Wind}\bar{C}) = 3,266,282,952.73$$

$$r = 0.994702 \approx 0.9947$$

Variable	REC	Solar	Wind
REC	1.0000	0.9998	0.9967
Solar	0.9998	1.0000	0.9947
Wind	0.9967	0.9947	1.0000

These very high correlations are expected because solar and wind are major components of aggregate renewable capacity. Using them simultaneously as regressors for REC would therefore create severe multicollinearity and partly reproduce an accounting identity.

Linear Time-Trend Regression for Renewable Capacity

$$\text{REC}_t = \alpha + \beta \text{TREND}_t + \varepsilon_t, \text{ where TREND} = 1, 2, \dots, 10$$

Step 1: Means

$$\bar{X} = (1 + 2 + \dots + 10) / 10 = 5.5$$

$$\bar{Y} = \text{REC}\bar{C} = 118,339.914 \text{ MW}$$

Step 2: Required sums

$$\Sigma(X - \bar{X})^2 = 82.5$$

$$\Sigma(X - \bar{X}) (Y - \bar{Y}) = 1,393,950.13$$

Step 3: Slope coefficient

$$\beta = \Sigma(X - \bar{X}) (Y - \bar{Y}) / \Sigma(X - \bar{X})^2$$

$$= 1,393,950.13 / 82.5$$

$$= 16,896.3652 \text{ MW}$$

Step 4: Intercept

$$\alpha = \bar{Y} - \beta \bar{X}$$

$$= 118,339.914 - (16,896.3652 \times 5.5)$$

$$= 25,409.9053$$

$$REC_t = 25,409.91 + 16,896.37 \text{ TREND}_t$$

Interpretation: On average, renewable-energy capacity increased by approximately 16,896 MW per year over the sample period.

R², Adjusted R², t-Test and F-Test for REC Trend

Sum of squares:

$$SST = \sum (Y - \bar{Y})^2 = 27,172,574,115.73$$

$$SSR = \sum (\hat{Y} - \bar{Y})^2 = 23,552,690,483.96$$

$$SSE = \sum (Y - \hat{Y})^2 = 3,619,883,631.76$$

$$\text{Check: } SST = SSR + SSE$$

$$R^2 = SSR / SST = 23,552,690,483.96 / 27,172,574,115.73 = 0.8668$$

$$\text{Adjusted } R^2 = 1 - (1 - 0.8668) \times [(10 - 1) / (10 - 1 - 1)] = 0.8501$$

Standard error and t-statistic:

$$MSE = SSE / (n - k - 1) = 3,619,883,631.76 / 8 = 452,485,453.97$$

$$SE(\beta) = \sqrt{[452,485,453.97 / 82.5]} = 2,341.94$$

$$t = 16,896.37 / 2,341.94 = 7.215$$

$$p = 0.00009$$

F-statistic:

With one regressor, $F = t^2$

$$F = (7.215)^2 = 52.052$$

$$\text{Prob}(F) = 0.00009$$

Statistic	Result
Trend coefficient	16,896.37 MW
t-statistic	7.215
p-value	0.00009
R ²	0.8668
Adjusted R ²	0.8501
F-statistic	52.052
Durbin-Watson	0.811

Log-Linear Growth Model

$$\ln (REC_t) = \alpha + \beta \text{TREND}_t + \varepsilon_t$$

Coefficient calculations:

$$\text{Mean } \ln (REC) = 11.594774$$

$$\sum (X - \bar{X})^2 = 82.5$$

$$\sum (X - \bar{X}) (\ln REC - \text{mean } \ln REC) = 11.537316$$

$$\beta = 11.537316 / 82.5 = 0.139846 \approx 0.13985$$

$$\alpha = 11.594774 - (0.139846 \times 5.5) = 10.82562$$

$$\ln(\text{REC}_t) = 10.8256 + 0.13985 \text{ TREND}_t$$

Exact annual growth rate:

$$\begin{aligned} g &= [\exp(\beta) - 1] \times 100 \\ &= [\exp(0.139846) - 1] \times 100 \\ &= (1.150097 - 1) \times 100 \\ &= 15.01\% \approx 15.0\% \text{ per year} \end{aligned}$$

Model fit and significance:

$$\begin{aligned} R^2 &= 0.971077 \approx 0.9711 \\ \text{Adjusted } R^2 &= 0.96746 \approx 0.9675 \\ \text{SE}(\beta) &= 0.0085329 \\ t &= 0.139846 / 0.0085329 = 16.389 \\ p &< 0.001 \\ \text{Durbin-Watson} &= 0.942 \end{aligned}$$

Technology-Specific Trend Models

The same OLS procedure is applied separately to REC, Solar and Wind. The estimated results are:

Dependent Variable	Annual Level Increase	Level R ²	Log-Trend Coefficient	Log R ²
Renewable capacity	16,896.37 MW	0.8668	0.13985	0.9711
Solar capacity	14,056.20 MW	0.8529	0.24968	0.9804
Wind capacity	2,491.18 MW	0.9075	0.05836	0.9517

Solar slope:

$$\begin{aligned} \beta_{\text{Solar}} &= \Sigma(\text{TREND} - \text{TREND}) (\text{SOLAR} - \text{SOLAR}) / 82.5 \\ &= 14,056.20 \text{ MW per year} \end{aligned}$$

Wind slope:

$$\begin{aligned} \beta_{\text{Wind}} &= \Sigma(\text{TREND} - \text{TREND}) (\text{WIND} - \text{WIND}) / 82.5 \\ &= 2,491.18 \text{ MW per year} \end{aligned}$$

Solar therefore exhibits the fastest proportional and absolute expansion among the technology-specific series considered.

Green Finance–Renewable Capacity Regression

Only the five years with observed GF values are used: 2017, 2018, 2019, 2020 and 2022.

Year	GF (₹ crore)	REC (MW)
2017	111,000	58,558.19
2018	137,000	70,651.43
2019	266,000	79,411.99
2020	352,000	88,255.30
2022	480,400	109,885.38

$$REC_t = \beta_0 + \beta_1 GF_t + \varepsilon_t$$

Means:

$$\bar{GF} = 269,280$$

$$\begin{aligned} \bar{REC} &= (58,558.19 + 70,651.43 + 79,411.99 + 88,255.30 + 109,885.38) / 5 \\ &= 81,352.458 \text{ MW} \end{aligned}$$

Slope:

$$\Sigma(GF - \bar{GF})(REC - \bar{REC}) = 11,624,647,040.80$$

$$\Sigma(GF - \bar{GF})^2 = 93,975,568,000$$

$$\begin{aligned} \beta_1 &= 11,624,647,040.80 / 93,975,568,000 \\ &= 0.1236986 \approx 0.12370 \end{aligned}$$

Intercept:

$$\begin{aligned} \beta_0 &= \bar{REC} - \beta_1 \bar{GF} \\ &= 81,352.458 - (0.1236986 \times 269,280) \\ &= 48,042.90 \end{aligned}$$

$$\hat{REC} = 48,042.90 + 0.12370 GF$$

R², t-Test and Economic Interpretation of the GF Regression

Model fit:

$$SSE = 61,680,266.54$$

$$R^2 = 0.95887 \approx 0.9589$$

$$\text{Adjusted } R^2 = 1 - (1 - 0.95887) \times (4/3) = 0.94516 \approx 0.9452$$

Coefficient test:

$$MSE = 61,680,266.54 / 3 = 20,560,088.85$$

$$SE(\beta_1) = 0.014791$$

$$t = 0.1236986 / 0.014791 = 8.363$$

$$p = 0.0036$$

$$F = t^2 = 69.939$$

Correlation:

$$r_{GF, REC} = \sqrt{R^2} \text{ (positive slope)}$$

$$= \sqrt{0.95887}$$

$$= 0.97922 \approx 0.979$$

Economic interpretation:

Coefficient = 0.12370 MW per ₹ crore

For an additional ₹10,000 crore: $\Delta REC = 0.12370 \times 10,000 = 1,237 \text{ MW}$

Therefore, ₹10,000 crore of additional measured green finance is associated with approximately 1,237 MW of additional renewable capacity in this five-observation sample.

This is an association, not a causal estimate, because the sample is extremely small, the GF series is not fully harmonised across years, and both GF and REC trend upward over time.

Sensitivity Regression: 2022 Mitigation Finance Only

The 2022 GF value is replaced by ₹371,200 crore (mitigation finance only). The five GF observations become 111,000; 137,000; 266,000; 352,000; and 371,200.

Mean GF:

$$GF = 1,237,200 / 5 = 247,440$$

Slope:

$$\Sigma(GF - \bar{GF})(REC - \bar{REC}) = 8,508,851,958.40$$

$$\Sigma(GF - \bar{GF})^2 = 57,406,672,000$$

$$\beta_1 = 8,508,851,958.40 / 57,406,672,000 \\ = 0.1482206 \approx 0.14822$$

Intercept:

$$\beta_0 = 81,352.458 - (0.1482206 \times 247,440) \\ = 44,676.75$$

$$REC = 44,676.75 + 0.14822 GF$$

Statistic	Sensitivity Result
GF coefficient	0.14822
t-statistic	3.983
p-value	0.0283
R ²	0.8410
Adjusted R ²	0.7880
Observations	5

The coefficient remains positive and statistically significant at the 5% level, but model fit declines materially from R² = 0.9589 to R² = 0.8410. This demonstrates sensitivity to the measurement choice for 2022.

Log-Log Green Finance Elasticity Model

$$\ln(REC_t) = \alpha + \beta \ln(GF_t) + \varepsilon_t$$

Means and sums:

$$\text{Mean } \ln(GF) = 12.358007$$

$$\text{Mean } \ln(REC) = 11.284175$$

$$\Sigma(\ln GF - \text{mean } \ln GF)^2 = 1.5432003$$

$$\Sigma(\ln GF - \text{mean } \ln GF)(\ln REC - \text{mean } \ln REC) = 0.5665413$$

Elasticity coefficient:

$$\beta = 0.5665413 / 1.5432003 \\ = 0.367121 \approx 0.3671$$

Intercept:

$$\alpha = 11.284175 - (0.367121 \times 12.358007) \\ = 6.747291 \approx 6.7473$$

$$\ln(REC) = 6.7473 + 0.3671 \ln(GF)$$

Statistic	Result
Elasticity coefficient	0.3671
t-statistic	6.430
p-value	0.0076
R ²	0.9323
Observations	5

Elasticity interpretation: a 1% increase in measured green finance is associated with approximately a 0.367% increase in renewable-energy capacity in the available five observations. This should be described as a descriptive elasticity, not as a causal structural estimate.

Sovereign Green Bond Regression

Only the four positive post-introduction SGB observations are used.

Year	SGB (₹ crore)	REC (MW)
2023	16,000	125,159.81
2024	20,000	143,644.49
2025	21,697.40	172,368.14
2026	15,000	239,661.00

Means:

$$\text{SGB} = (16,000 + 20,000 + 21,697.40 + 15,000) / 4 = 18,174.35$$

$$\text{REC} = (125,159.81 + 143,644.49 + 172,368.14 + 239,661.00) / 4 = 170,208.36$$

Slope:

$$\Sigma(\text{SGB} - \text{SGB}) (\text{REC} - \text{REC}) = -163,402,989.43$$

$$\Sigma(\text{SGB} - \text{SGB})^2 = 30,549,175.07$$

$$\beta_1 = -163,402,989.43 / 30,549,175.07$$

$$= -5.34885 \approx -5.3489$$

Intercept:

$$\beta_0 = 170,208.36 - (-5.34885 \times 18,174.35)$$

$$= 267,420.25$$

$$\text{REC} = 267,420.25 - 5.3489 \text{ SGB}$$

Statistic	Result
SGB coefficient	-5.3489
t-statistic	-0.511
p-value	0.660
R ²	0.1156
Adjusted R ²	-0.3267
Observations	4

Because $p = 0.660 > 0.05$, the coefficient is statistically insignificant. The negative sign should not be interpreted as evidence that sovereign green bonds reduce renewable capacity; it is driven by an extremely short four-observation post-introduction sample in which annual bond mobilisation fluctuates while REC is a cumulative stock variable.

Durbin-Watson Statistic

$$\text{DW} = \sum_{t=2}^n (e_t - e_{t-1})^2 / \sum_{t=1}^n e_t^2$$

Applying the formula to the residuals of the linear REC trend regression gives $\text{DW} = 0.811$. Applying it to the log-REC trend model gives $\text{DW} = 0.942$. Values substantially below 2 indicate possible positive residual serial dependence, although inference is weak with only ten annual observations.

Diagnostic Tests

Diagnostic	Reported Result	Interpretation
Jarque–Bera normality	JB = 1.993; p = 0.369	No evidence against residual normality
Breusch–Pagan heteroscedasticity	LM p = 0.066; F p = 0.078	Borderline but not significant at 5%
Breusch–Godfrey LM, lag 1	LM p = 0.068; F p = 0.104	Possible persistence; not significant at 5%
Durbin–Watson	0.942	Suggests positive serial dependence
ADF on ln (REC), trend included	ADF = 1.715; p ≈ 1.000	Cannot reject non-stationarity in the short sample

$$JB = (n/6) \times [S^2 + (K - 3)^2/4]$$

Jarque–Bera illustration:

Using the log-trend residuals: $S \approx 1.076$ and $K \approx 3.391$

$$JB = (10/6) \times [(1.076)^2 + (3.391 - 3)^2/4]$$

≈ 1.993, with p ≈ 0.369

Technical note: the ADF result is highly specification-sensitive in such a short sample. The exact statistic should be rechecked using the same software, deterministic terms and lag-selection rule before final publication.

Consolidated Econometric Results

Model	Key Coefficient	t-statistic	p-value	R ²	Interpretation
REC linear trend	16,896.37 MW/year	7.215	0.00009	0.8668	Strong positive annual trend
ln (REC) trend	0.13985	16.389	<0.001	0.9711	≈15.0% annual growth
GF → REC level	0.12370	8.363	0.0036	0.9589	Positive exploratory association
GF → REC sensitivity	0.14822	3.983	0.0283	0.8410	Positive; measurement-sensitive
ln (GF) → ln (REC)	0.3671	6.430	0.0076	0.9323	Descriptive elasticity
SGB → REC	−5.3489	−0.511	0.660	0.1156	Insignificant; N = 4

Brief Note on the Hypotheses

Green Finance and Renewable-Energy Development in India

The hypotheses examine whether green-finance mobilisation is statistically associated with renewable-energy development in India, whether total renewable, solar and wind capacity show

significant positive time trends, and whether sovereign green bonds are associated with renewable-energy development. Each null hypothesis (H0) is paired with an alternative hypothesis (H1).

Green Finance and Renewable-Energy Capacity

H01: Green-finance mobilisation has no statistically significant positive relationship with renewable-energy capacity in India.

H11: Green-finance mobilisation has a positive and statistically significant relationship with renewable-energy capacity in India.

Brief interpretation: Tests the basic level relationship between measured green-finance mobilisation and installed renewable-energy capacity.

Green-Finance Elasticity

H02: A percentage increase in green finance is not associated with a statistically significant positive percentage increase in renewable-energy capacity.

H12: A percentage increase in green finance is associated with a positive and statistically significant percentage increase in renewable-energy capacity.

Brief interpretation: Examines percentage responsiveness through the log-log model; the coefficient represents the percentage change in renewable-energy capacity associated with a 1% change in measured green finance.

Time Trend in Total Renewable-Energy Capacity

H03a: Total renewable capacity does not exhibit a statistically significant positive time trend.

H13a: Total renewable capacity exhibits a positive and statistically significant time trend.

Brief interpretation: Tests whether aggregate renewable-energy capacity shows a systematic upward trend over 2017-2026.

Time Trend in Solar Capacity

H03b: Solar capacity does not exhibit a statistically significant positive time trend.

H13b: Solar capacity exhibits a positive and statistically significant time trend.

Brief interpretation: Evaluates the solar growth path separately so that technology-specific expansion is not hidden within aggregate renewable capacity.

Time Trend in Wind Capacity

H03c: Wind capacity does not exhibit a statistically significant positive time trend.

H13c: Wind capacity exhibits a positive and statistically significant time trend.

Brief interpretation: Tests whether wind capacity has also recorded a statistically significant upward movement during the study period.

Sovereign Green Bonds and Renewable-Energy Development

H04: Sovereign-green-bond mobilisation has no statistically significant positive relationship with renewable-energy development in India.

H14: Sovereign-green-bond mobilisation has a positive and statistically significant relationship with renewable-energy development in India.

Brief interpretation: Assesses the possible association between sovereign-green-bond mobilisation and renewable-energy development. Because the sovereign-green-bond history is very short, this hypothesis is exploratory and requires cautious interpretation.

Overall Note

The hypotheses follow a logical sequence: direct green-finance association, elasticity, time trends in total renewable, solar and wind capacity, and finally the specific role of sovereign green bonds. This structure is consistent with the study's objectives and allows each empirical relationship to be tested separately.

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