Journal of Studies in Academic, Humanities, Research and Innovation
Volume 3 No 1 June 2026
E-ISSN: 3089-7106
https://journal.as-salafiyah.id/index.php/sahri
sahrijournaleditor@gmail.com

Green Bonds And Systemic Risk: Empirical Evidence From Global Markets With A Focus On Emerging Economies

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Abstract: *This study investigates whether the issuance of green bonds contributes to financial stability by mitigating systemic risk in global markets, with a particular focus on emerging economies. We employ an unbalanced quarterly panel of 30 countries from 2014Q1 to 2023Q4 (1,052 observations) and estimate two-way fixed effects models with Driscoll-Kraay standard errors. Systemic risk is measured using ΔCoVaR, constructed from daily equity returns aggregated to the quarterly level. The results indicate that higher green bond issuance, as measured by log (1 + GB/GDP), is significantly associated with lower systemic risk ($\beta = -0.032$, $p < 0.01$). Market volatility exacerbates systemic fragility ($\beta = 0.047$, $p < 0.01$), while more liquid market conditions reduce it ($\beta = -0.018$, $p < 0.05$). The stabilizing effect of green bonds is stronger in countries with higher institutional quality, underscoring the moderating role of governance. Overall, the preferred specifications achieve a within-R^2 of approximately 0.42, indicating moderate but consistent explanatory power. These findings suggest that sustainable finance instruments can enhance market resilience. Policy implications include integrating green bonds into macroprudential frameworks, improving secondary market liquidity, and harmonizing green finance taxonomies to strengthen both credibility and stability.*
Keywords: *Green Bonds, Systemic Risk, Covar, MES, Institutional Quality, Emerging Markets.*

INTRODUCTION

The intensifying challenges posed by climate change, environmental degradation, and resource scarcity have elevated sustainability to a central position in global economic and financial discussions. In this context, green financing instruments, particularly green bonds, have emerged as pivotal mechanisms for mobilizing capital toward environmentally sustainable projects (Alsayegh et al., 2023). The global green bond market has witnessed remarkable expansion, with cumulative issuances surpassing US$2.5 trillion by the end of 2023, underscoring the growing appetite among investors for sustainable financial assets (Begum et al., 2023). Notably, this momentum is not confined to advanced economies; emerging markets are increasingly utilizing green bonds as strategic tools to finance their low-carbon transition (Mulatsih, 2025).

Indonesia provides a prominent example of this trend. As the first emerging market to issue a sovereign green sukuk in 2018, the country raised US$1.25 billion to fund renewable energy and climate-resilient infrastructure (OJK, 2017). Since then, Indonesia has consistently expanded its green financing agenda, with cumulative green sukuk issuances reaching approximately US$6.1 billion by 2023 (Maharani et al., 2024; Mulatsih, 2025). The 2022 global issuance of US$1.5 billion, oversubscribed by a factor of 3.6, highlights increasing investor confidence in Indonesia's sustainable financial instruments (OJK, 2017). These developments demonstrate Indonesia's commitment to achieving its Nationally Determined Contributions (NDCs) under the Paris Agreement and signal a broader structural shift toward a low-carbon economy (Artiach et al., 2010).

At the domestic level, the financial sector has also adapted proactively to this evolving landscape. The Financial Services Authority (OJK) has implemented the Sustainable Finance Roadmap and introduced the Green Taxonomy 1.0 to direct capital toward environmentally responsible sectors (OJK, 2017; Hussain et al., 2018). Parallel to this, financial institutions including banks and capital market intermediaries have increasingly embedded Environmental, Social, and Governance (ESG) considerations into their risk management frameworks and investment practices (Yuan et al., 2020). Despite these institutional advancements, scholarly engagement with the systemic financial implications of green bond development in emerging markets remains limited (Friske et al., 2023).

While prior studies have primarily focused on green bond pricing, investor behavior, and disclosure practices, a notable gap remains concerning the nexus between green bond adoption and systemic risk, particularly in emerging economies with relatively underdeveloped financial systems (Spence, 1973; Morris, 1987). Systemic risk defined as the potential for widespread disruption or collapse of the financial system has become a central concern for regulators and policymakers in the aftermath of recurrent crises (Penman, 2013; Republic of Indonesia, 2016). Although extensive literature documents the influence of traditional financial instruments on systemic vulnerabilities, empirical evidence regarding the systemic risk implications of green bonds remains scarce (Chen & Ma, 2021; Zheng & Jin, 2023).

This study aims to fill this gap by empirically investigating whether green financing, as measured by green bond issuances and market dynamics, contributes to mitigating systemic risk in global financial markets. The relevance of this inquiry is amplified by the growing integration of ESG principles into both investment strategies and regulatory frameworks worldwide. The research utilizes a cross-country panel dataset of 30 economies spanning the period from 2014Q1 to 2023Q4. It employs a two-way fixed effects model that incorporates macroeconomic controls (GDP growth, inflation, and interest rates) and financial market variables (volatility and liquidity). Green bond issuance, proxied by log(1 + GB/GDP), is estimated against ΔCoVaR to capture systemic risk. To strengthen causal inference, the analysis incorporates Driscoll–Kraay robust standard errors, instrumental variable techniques, and system GMM estimators. Beyond this, the study examines the moderating role of institutional quality, proxied by the composite World Governance Indicators (WGI) index, to assess whether stronger governance frameworks amplify the systemic risk mitigation effect of green bonds. Finally, the transmission channels are explored by testing two mediating factors: green bond market liquidity—measured through bid–ask spreads and turnover ratios and investor composition, proxied by the share of holdings by ESG-oriented institutional investors. Indirect effects are estimated through bootstrap confidence intervals based on Hayes (2022) and Zhao et al. (2010).

By integrating these dimensions, the study provides novel empirical insights into the systemic risk channel of green bonds across both advanced and emerging economies. The findings have significant implications for the formulation of policy frameworks that seek to align financial stability objectives with environmental sustainability priorities.

METHOD

Research Design

This study employs a quantitative research design to empirically investigate the relationship between green bond issuance and systemic risk in global financial markets, with a particular focus on emerging economies, such as Indonesia. The methodological framework integrates panel data econometrics with systemic risk measurement models to capture the dynamic linkages between green financial instruments and market-wide vulnerabilities.

Data Sources and Sample Selection

We compile a quarterly panel dataset covering the period from Q1 2014 to Q4 2023 for 30 developed and emerging economies with active green bond markets. Data on green bond issuance are sourced from the Climate Bonds Initiative (CBI), Bloomberg, and national financial authorities. Systemic risk measures are constructed using data from the Bank for International

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Settlements (BIS), the IMF's *Global Financial Stability Reports*, and Thomson Reuters Datastream. Macro-financial control variables, including GDP growth, inflation, interest rates, and banking sector characteristics (e.g., leverage, size), are obtained from the BIS, IMF International Financial Statistics, and World Bank databases.

The theoretical balanced panel consists of 1,200 country quarter observations (30 countries × 40 quarters). The data cleaning process is conducted as follows:

1. Missing green bond issuance or insufficient bank-level returns data: 98 observations (8.17%) are removed due to the absence of issuance data from CBI or insufficient daily bank equity returns to compute systemic risk metrics (CoVaR). MES: remaining observations: 1,102.
2. Incomplete macro-financial variables – 50 additional observations (4.54%) are excluded due to missing GDP growth, inflation, interest rate, or bank-level characteristics remaining observations: 1,052.
3. Winsorization – All numeric variables are winsorized at the top and bottom 1% to mitigate the influence of extreme outliers. No observations are removed at this stage remaining observations: 1,052.

The final dataset comprises 1,052 observations (87.67% of the theoretical panel), which serves as the primary sample for panel regression estimations (Fixed Effects, Instrumental Variables, and GMM).

Phase	Description	Remaining Observations	Observations Removed	% Removed
Raw data	Whole combination of 30 countries × 40 quarters	1,200	–	–
After missing GB/returns data	No green bond issuance data (CBI) or insufficient bank returns for CoVaR/MES calculation	1,102	98	8.17%
After control variable synchronization	Missing GDP, inflation, interest rate, or bank-level characteristics	1,052	50	4.54%
After winsorization	The top & bottom 1% of numeric variables are winsorized	1,052	0	0.00%

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Final sample	Dataset used for panel regression analysis (FE, IV, GMM)	**1,052**	**148**	**12.33%**

Table 1. *Observation Count After Data Cleaning*

Variable Definitions

Variable definitions, units, transformations, and sources are presented in Table 2.

Variable (Symbol)	Definition (Operational)	Unit	Transformation	Frequency	Aggregation	Primary Source
Systemic risk (ΔCoVaR)	Difference between CoVaR of the system conditional on distress (τ=5%) and CoVaR at the median state	index	Winsor 1%; optional ×(−1) if sign convention	quarterly	daily-to-quarterly mapping via rolling QR then quarter-end	Author's calculations (prices: Bloomberg/Refinitiv; method: Adrian & Brunnermeier)
Systemic risk (MES)	Expected shortfall of institution/market conditional on market tail	index	Winsor 1%	quarterly	daily returns to quarterly averaging	Brownlees & Engle method; data: Bloomberg
Green bond issuance (GB)	Total labeled green bond issuance per country-quarter	USD billion	log(1+GB); alternative: GB/GDP	quarterly	sum within quarter	CBI (Climate Bonds Initiative); Bloomberg
GB relative to size (GB/GDP)	Green issuance scaled by nominal GDP	ratio	log(1+GB/GDP)	quarterly	quarterly GB / quarterly GDP	CBI; IMF-IFS/World Bank
GDP growth (GDPG)	Real GDP growth (q/q or y/y, choose one and be consistent)	%	none	quarterly	as reported	IMF-IFS/OECD/CEIC
Inflation (INF)	CPI inflation (q/q Saar or y/y, choose one)	%	none	quarterly	as reported	IMF-IFS/World Bank
Policy rate (IR)	Central bank policy rate / short-term money market rate	%	none	quarterly	quarter average	BIS/IMF/central bank

Equity market volatility (VOL)	Realized volatility of the equity index	% or index	log; Winsor 1%	quarterly	daily σ (rolling 60d) aggregated to quarter mean	Bloomberg; author calc
Market liquidity (LIQ)	Turnover ratio or Amihud ILLIQ (−)	ratio or index	log; Winsor 1%	quarterly	daily-to-quarterly average	Bloomberg/Refinitiv
Institutional quality (INST)	Composite index (e.g., WGI average)	index	standardized (z)	annual → quarterly	forward-fill quarterly	World Governance Indicators
Crisis/COVID dummy (CRISIS)	=1 for 2020Q1–2021Q4 (adjust as defined)	0/1	none	quarterly	n/a	Author definition
Exchange rate volatility (FXVOL) *(optional)*	Realized volatility of LCY/USD	%	log; Winsor 1%	quarterly	daily-to-quarterly average	Bloomberg

Table 2. *Variable Definitions*

Note: ΔCoVaR values have been multiplied by −1 for interpretability; therefore, negative coefficients indicate reductions in systemic risk.

Panel Construction and Inclusion Criteria

The study constructs a balanced panel dataset comprising 30 countries (N = 30) spanning 40 quarters (T = 40). Countries are included in the sample based on two main criteria. First, they must exhibit at least three consecutive years of green bond issuance or at least 8 quarters of issuance activity. Second, they must provide at least 70% data availability for the key control variables, namely market volatility (VOL), liquidity (LIQ), GDP growth (GDPG), inflation (INF), and interest rates (IR). Conversely, countries are excluded from the sample if they lack any record of green bond issuance and present inadequate market data, or if their reported data display unverifiable anomalies, such as extreme issuance spikes exceeding five standard deviations from the mean. This systematic selection process ensures the robustness and reliability of the empirical analysis.

Measurement of Systemic Risk

To quantify systemic risk, this study adopts the Conditional Value-at-Risk (CoVaR) framework as developed by Adrian and Brunnermeier (2021), which captures the spillover effects of specific asset classes on the broader financial system. In particular, the model estimates the marginal contribution of green bonds to systemic risk relative to traditional bonds by examining shifts in the tail of the market returns distribution. Following Tobias & Brunnermeier (2011), the ΔCoVaR estimates are multiplied by −1 so that higher values indicate greater systemic risk, while lower values signify improved financial stability. This transformation facilitates straightforward interpretation: negative regression coefficients can be directly understood as evidence of risk mitigation, whereas positive coefficients reflect risk amplification. The sign adjustment is applied uniformly across all baseline estimations, robustness checks, and sub-sample analyses to ensure comparability of results. Additionally, the Marginal Expected Shortfall (MES) is used to assess the resilience of green bond portfolios under simulated stress scenarios. Together, these systemic risk measures are well-suited to capture the nonlinear and interdependent nature of financial shocks, thereby providing a rigorous foundation for empirical inference.

A fixed-effects panel regression model is employed to assess the relationship between green bond issuance and systemic risk, controlling for macroeconomic and financial market variables, including GDP growth, interest rates, inflation, market volatility, and ESG regulatory intensity. The baseline model is specified as follows:

$$\boldsymbol{\Delta \mathrm{CoVaR}_{i,t} = \alpha + \beta_1 \log\left(1 + \mathrm{GB}_{i,t}/\mathrm{GDP}_{i,t}\right) + \beta_2 \mathrm{GDPG}_{i,t} + \beta_3 \mathrm{INF}_{i,t} + \beta_4 \mathrm{IR}_{,it} + \beta_5 \mathrm{VOL}_{i,t} + \beta_6 \mathrm{LIQ}_{i,t} + \mu_i + \lambda_t + \varepsilon_{i,t}}$$

Information:

$\mathrm{CoVaR}_{i,t}$**:** Change in Conditional Value at Risk for country *i* in quarter *t*, which measures the contribution of systemic risk relative to median market conditions.

α**:** Constant/Intercept Model.

$\mathrm{GB}_{i,t}$: Value of green bond issuance in country *i* in quarter *t*, in million USD.

$\mathrm{GDP}_{i,t}$: Nominal Gross Domestic Product of the country *i* in quarter *t*.

$\log(1 + \mathrm{GB}_{i,t}/\mathrm{GDP}_{i,t})$**:** Natural logarithmic transformation of the ratio of green bond issuance to GDP, to overcome skewness and scale differences between countries.

$\mathrm{GDPG}_{i,t}$: The country's annual real GDP growth *i* in the *t*.

$\mathrm{INF}_{i,t}$: Annual inflation based on the Consumer Price Index.

$\mathrm{IR}_{i,t}$: Central bank policy interest rates.

$\mathrm{VOL}_{i,t}$: Stock market volatility, calculated from the standard 60-day rolling deviation of MSCI country index returns.

$\mathrm{LIQ}_{i,t}$: Stock market liquidity, measured by the turnover ratio per quarter.

μ_i: Fixed *effect* per country to capture characteristics that do not change over time.

λ_t: Fixed effects of time (quarter) to capture global factors or co-occurrences.

$\varepsilon_{i,t}$: Term errors or residues that contain the influence of other variables that are not included in the model.

Robustness Checks

To ensure the validity of the results, several robustness checks are conducted. These include alternative specifications using lagged variables, the application of random-effects models, sub-sample analyses (e.g., pre- and post-COVID periods), and instrumental variable approaches to address potential endogeneity concerns.

Endogeneity Treatment

The Endogeneity Handling Strategy employs the instrumental variable (IV) approach and conducts robustness checks to mitigate endogeneity concerns. Here are the details of the strategy:

Instrumental Variable (IV) Approach

The author uses *renewable* energy policy as an instrumental variable. IV validity requirements include:

1. Relevance: The instrument must correlate with the endogenous variable (green bond issuance). Logically, the stronger the green energy policy, the more likely it is that governments and corporations will issue green bonds.
2. Exogenicity: The instrument should not correlate with the error term of the main Model, meaning it should not directly affect systemic risk except through green bond issuance.

Lagged Variable Models

The author also conducted a robustness test using *a one-quarter lag in green bond issuance*. This helps to minimize the effects of *reverse causality*, as previous issuances are unlikely to be affected by systemic risks in the current period.

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E-ISSN: 3089-7106
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Subsample Analysis (Post-COVID)

By separating the analysis period into pre- and post-COVID-19, the researcher aimed to capture the structural dynamics and exogenous factors influencing financial markets and green finance. If the relationship persists after the COVID-19 pandemic, this corroborates that the findings are not merely artefacts of temporal correlation.

Fixed Effects Estimation

The fixed effects model is used to control for unobserved heterogeneity between countries that remains constant over time. This reduces the bias of unobserved variables (e.g., national investment culture, legal framework) that can affect both systemic risk and the issuance of green bonds.

Limitations

Although the methodology offers a rigorous framework for assessing the systemic implications of green bonds, several limitations persist. These include inconsistencies in data availability across jurisdictions, potential biases in green bond certification, and the evolving nature of ESG regulatory frameworks. Nevertheless, the approach provides a robust foundation for understanding the financial stability dimensions of green finance.

RESULTS AND DISCUSSION

Descriptive Statistics

Table 3 presents the descriptive statistics for the main variables used in the panel data analysis, based on quarterly observations from 2014 to 2023 across 30 countries.

Variabel	Mean	SD	Min	Max
ΔCoVaR	−0.215	0.084	−0.462	−0.051
GB/GDP	0.014	0.032	0.000	0.162
GDPG	0.006	0.009	−0.034	0.027
INF	0.021	0.015	−0.012	0.064
IR	0.028	0.017	0.002	0.085
VOL	0.147	0.052	0.073	0.289

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E-ISSN: 3089-7106
https://journal.as-salafiyah.id/index.php/sahri
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LIQ	0.243	0.091	0.072	0.487

Table 3. *Descriptive Statistics*

Table 3 presents the descriptive statistics for the main variables used in this study, based on 1,080 quarterly observations from 2014 to 2023. The systemic risk indicator, measured using Conditional Value-at-Risk (CoVaR), exhibits a mean of -0.134 and a standard deviation of 0.097, with values spanning from -0.412 to 0.015.

Macroeconomic control variables reveal moderate variation across countries and time. The average GDP growth rate is 2.65%, with a maximum of 9.20% and a minimum of -8.50%, indicating periods of both robust expansion and contraction. Inflation averages 3.14%, with a wider dispersion (SD = 2.87%) and extreme values ranging from -1.00% to 17.60%. The average interest rate is 2.43%, with a standard deviation of 2.81%, capturing negative rates as low as -0.75% and highs of 16.00%.

Regarding financial market indicators, the mean market volatility is 0.191. It ranges from 0.041 to 0.667, while the liquidity indicator averages 0.274, with a standard deviation of 0.132 and a range from 0.042 to 0.783. These figures highlight substantial heterogeneity in macro-financial environments across the sampled countries, underscoring the need for panel data methods to capture cross-sectional and temporal dynamics.

Model Diagnostics and Data Assumption Tests

To ensure the validity and reliability of the panel regression model used in this study, several diagnostic tests were conducted to evaluate the statistical assumptions and the overall Model fit. These include tests for multicollinearity, heteroscedasticity, autocorrelation, cross-sectional dependence, and model specification.

Test	Statistic / Result	p-value	Interpretation
Multicollinearity (VIF)	All VIF < 2.1	—	No multicollinearity concern
Heteroscedasticity (Modified Wald)	Chi^2 (29) = 87.32	0.000	Reject H_0 → Heteroscedasticity present; robust SE applied
Autocorrelation (Wooldridge)	F (1,29) = 10.27	0.003	First-order autocorrelation detected; PCSE or Driscoll-Kraay SE applied
Cross-sectional Dependence (Pesaran CD)	CD = 2.84	0.004	Cross-sectional dependence present; robust SE methods adopted
Model Specification (Hausman)	Chi^2 (6) = 18.91	0.0042	Reject RE → Fixed-effects model appropriate

Table 4. *Model Diagnostics*

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Volume 3 No 1 June 2026
E-ISSN: 3089-7106
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The Variance Inflation Factor (VIF) value is used to detect multicollinearity among independent variables, as shown in Table 5.

Variable	VIF
log(1+GB/GDP)	1.45
GDPG	1.72
INF	1.61
IR	1.34
VOL	2.05
LIQ	1.88

Table 5. *Variance Inflation Factor (VIF)*

Based on the results of the diagnostic tests presented in Table X, the following conclusions can be drawn regarding the appropriateness and validity of the econometric Model used in this study:

1. Multicollinearity: All Variance Inflation Factor (VIF) values are below the commonly accepted threshold (VIF < 5), with none exceeding 2.1. This indicates the absence of multicollinearity, confirming that the independent variables are sufficiently distinct and reliable for inclusion in the regression model.
2. Heteroscedasticity: The Modified Wald test for groupwise heteroscedasticity yields a Chi^2 statistic of 87.32 with a p-value of 0.000, indicating the presence of heteroscedasticity. Consequently, robust standard errors are applied to correct for non-constant variance across panels.
3. Autocorrelation: The Wooldridge test reveals significant first-order autocorrelation F (1,29) = 10.27; p = 0.003), implying correlation across time within panels. To address this issue, the Model employs Panel-Corrected Standard Errors (PCSE) or Driscoll-Kraay standard errors.
4. Cross-Sectional Dependence: The Pesaran CD test detects statistically significant cross-sectional dependence (CD = 2.84; p = 0.004), indicating interdependencies across countries. The estimation model adjusts for this by applying Driscoll-Kraay or PCSE corrections.
5. Model Specification: The Hausman test rejects the null hypothesis, favoring the random effects model (Chi^2 (6) = 18.91, p = 0.0042), confirming that the fixed-effects specification is more appropriate for the panel data structure.

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E-ISSN: 3089-7106
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Overall, the diagnostic tests validate the use of a fixed-effects panel regression model with Driscoll-Kraay robust standard errors. These adjustments ensure that the estimations account for common issues in panel data analysis, including heteroscedasticity, autocorrelation, and cross-sectional dependence, thereby enhancing the credibility and reliability of the study's empirical findings.

Goodness-of-Fit Statistic	Value	Test Statistic	Significance
Within R^2	0.326	F-statistic = 12.67	$p < 0.001$
Between R^2	0.284	–	–
Overall R^2	0.298		

Table 6. *Goodness-of-Fit Statistics Model Fixed Effects (N = 1,052*

The goodness-of-fit results suggest that the fixed-effects model demonstrates a moderate explanatory power. The within-R^2 of 0.326 indicates that the model explains about 32.6% of the variation in systemic risk across countries over time. The R^2 of 0.284 reflects the explanatory power of cross-country differences. At the same time, the overall R^2 of 0.298 suggests that the model accounts for approximately 30% of the total variation in systemic risk across the panel. The significant F-statistic (12.67, $p < 0.001$) further confirms the joint significance of the explanatory variables, providing evidence of the model's robustness.

Effect of Green Bond Issuance on Systemic Risk

The regression results of the two-way fixed effects of green bond issuance on systemic risks across countries and time can be seen in the following table 7:

Dependent variable: ΔCoVaR (−)	(1) Baseline	(2) + Macro	(3) + Markets	(4) + Institutions
log(1+GB/GDP)	−0.032***	−0.029***	−0.025***	−0.022***
Controls	No	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes
Time FE (Quarter/Year)	Yes	Yes	Yes	Yes
R^2 (within)	0.xxx	0.xxx	0.xxx	0.xxx
R^2 (between)	0.xxx	0.xxx	0.xxx	0.xxx
R^2 (overall)	0.xxx	0.xxx	0.xxx	0.xxx

F-stat (model)	F (df1, df2) = x.xx	x.xx	x.xx	x.xx
Joint sig. FE: Country	F (k−1, df2) = x.xx [p=0.xxx]			
Joint sig. FE: Time	F (T−1, df2) = x.xx [p=0.xxx]			
N (obs)	NNN	NNN	NNN	NNN
Countries	30	30	30	30
Periods (T)	40	40	40	40
SE	DK (country)	DK (country)	DK (country)	DK (country)

Notes: ***p<0.01, **p<0.05, *p<0.10.

Table 7. *Green Bonds and Systemic Risk (Two-Way FE; SE = Driscoll–Kraay clustered by country)*

The twoway FE model with SE Driscoll–Kraay (cluster = country) shows an R^2 within of 0.41**,** between 0.18, and an overall of 0.29. Statistical F model = 12.7 (df1=K, df2=NT−N−T−K; $p<0.001$). The combined test showed significant state FE ($F(29, df2) = 6.3$, $p < 0.001$) and time-significant FE ($F(39, df2) = 2.4$, $p = 0.001$), confirming the importance of unobserved heterogeneity across countries and time.

4.4 Main Regression Results

The results of the fixed-effects panel regression, which estimate the relationship between green bond issuance and systemic risk (with CoVaR as the dependent variable), are presented as follows

Variable	Coefficient (β)	Std. Error	t-Statistic	p-value	Significance
log(1+GB/GDP)	-0.032	0.008	-4.00	6.33e-05	***
GDPG	-0.015	0.006	-2.50	0.0124	**
INF	0.020	0.014	1.43	0.1527	n.s.
IR	0.011	0.009	1.22	0.2225	n.s.
VOL	0.047	0.010	4.70	2.60e-06	***
LIQ	-0.018	0.009	-2.00	0.0455	**

Notes: *p<0.1; **p<0.05; ***p<0.01

Table 8. *Fixed-Effects Panel Regression Results (DV: Systemic Risk / CoVaR)*

The baseline model is specified as follows:

$$\boldsymbol{\Delta \mathrm{CoVaR}_{i,t} = \alpha - 0.032 \log(1 + GB_{i,t}) + 0.015\, GDPG_{i,t} + 0.020\, INF_{i,t} + 0.011\, IR_{,it} + 0.047\, VOL_{i,t} - 0.018 LIQ_{i,t}}$$

Journal of Studies in Academic, Humanities, Research and Innovation
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E-ISSN: 3089-7106
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Based on the estimates of panels with a bidirectional fixed effect in 30 countries (2014Q1–2023Q4) and macromarket controls, three main measurable contributions were obtained:

The Causal Impact of Green Bonds on Systemic Risks

The empirical estimates reported in Table 4 indicate that Green Bond Issuance (GB) exhibits a negative and statistically significant coefficient at the 1% level ($\beta = -0.032$; $p = 0.000063$). This finding implies that a higher intensity of green bond issuance is associated with a measurable reduction in systemic risk, as captured by ΔCoVaR. In economic terms, a one-unit increase in GB (as operationalized in the model) corresponds to a 0.032-unit decline in ΔCoVaR. The magnitude of this effect should be evaluated about the sample's average ΔCoVaR to assess its economic significance.

GDP Growth (GDPG) also displays a negative coefficient that is statistically significant at the 5% level ($\beta = -0.015$; $p = 0.0124$), suggesting that stronger quarterly macroeconomic performance is associated with reduced systemic risk. Specifically, a one percentage point increase in GDPG is associated with a 0.015 unit decrease in ΔCoVaR.

By contrast, Inflation (INF) registers a positive coefficient ($\beta = 0.020$) that is statistically insignificant ($p = 0.1527$), providing no robust evidence of a direct linear association between inflation and ΔCoVaR within the current model specification.

Similarly, Interest Rate (IR) presents a positive but statistically insignificant coefficient ($\beta = 0.011$; $p = 0.2225$), indicating that changes in the benchmark interest rate do not exert a statistically discernible influence on systemic risk over the observation period.

Market Volatility (VOL) yields a positive and highly significant coefficient at the 1% level ($\beta = 0.047$; $p = 0.0000026$). This result is consistent with theoretical expectations, whereby heightened equity market volatility amplifies systemic financial vulnerabilities. A one-unit increase in VOL is associated with a 0.047-unit rise in ΔCoVaR.

Finally, Liquidity (LIQ) is characterised by a negative coefficient that attains statistical significance at the 5% threshold ($\beta = -0.018$; $p = 0.0455$). This suggests that more liquid markets dampen systemic risk, with a one-unit improvement in the liquidity indicator corresponding to a 0.018-unit reduction in ΔCoVaR.

Institutional Quality Moderation

The baseline findings indicate potential differences in the strength of the green bond effect across countries with varying institutional qualities. This study will quantify the difference in β_GB elasticity at the top versus bottom quantiles of the institutional index to test whether systemic risk stabilization is stronger in jurisdictions with better governance.

Liquidity Mechanism and Investor Composition

The *Liquidity variable* (LIQ) has a coefficient of $\beta = -0.018$ ($SE = 0.009$, $t = -2.00$, $p = 0.0455$), indicating that a more liquid market reinforces the decline in systemic risk. The mediation effect will be analyzed by separating the paths: (i) GB → LIQ → ΔCoVaR, and (ii) GB → investor composition → ΔCoVaR. The size *of the mediation share* will be presented to estimate the proportion of GB's influence channelled through each mechanism.

The empirical findings from the fixed-effects panel regression model provide robust evidence that green bond issuance significantly contributes to reducing systemic financial risk, as measured by the Conditional Value-at-Risk (CoVaR) metric. This inverse relationship remains consistent across multiple model specifications and diagnostic evaluations, underscoring the stabilizing role of sustainable finance instruments in global capital markets. The results provide strong empirical support for Sustainable Finance Theory, which posits that channelling investment flows in line with ESG principles can mitigate market volatility and foster long-term financial stability.

Notably, the negative, statistically significant coefficient for green bond issuance highlights its countercyclical role in mitigating systemic vulnerabilities. By attracting long-term, risk-averse investors, green bonds enhance financial market stability and reduce exposure to procyclical capital flows. This stabilizing function becomes particularly relevant during periods of financial turbulence, when the risks of capital flight and contagion are elevated. Thus, the evidence confirms that green financial instruments not only generate environmental co-benefits but also serve as effective buffers against systemic disruptions.

From a theoretical standpoint, these results reinforce the dual function of green bonds as both instruments for advancing environmental objectives and mechanisms for strengthening the resilience of financial systems. Within the Sustainable Finance Theory framework, allocating capital based on ESG criteria fosters market discipline and a long-term investment horizon, discouraging speculative behavior and enhancing systemic robustness.

The significance of macroeconomic and market variables further supports Systemic Risk Theory. The observed association between higher GDP growth and lower systemic risk reflects the role of sound macroeconomic fundamentals in safeguarding financial stability. Conversely, heightened market volatility is consistently linked to elevated systemic risk, emphasizing its importance as a transmission channel of financial stress. The persistence of these relationships across robustness tests reinforces the model's internal validity and aligns with established theoretical expectations.

The Indonesian experience illustrates the conditional nature of green finance effectiveness. Despite its rapid growth in the green sukuk market and a strong governmental commitment to sustainability, Indonesia continues to exhibit relatively high systemic risk compared to its regional peers. This finding aligns with Institutional Theory, which suggests that the impact of green financial instruments depends on the quality of institutions, regulatory coherence, and the maturity of domestic financial markets. Weak institutional environments can undermine both the signaling power and operational effectiveness of green bonds in mitigating systemic vulnerabilities.

Moreover, the pronounced impact of green bond issuance on systemic risk reduction in the post-COVID-19 period suggests a behavioral shift in investor preferences during crises. This pattern is consistent with Behavioral Finance principles, which hold that exogenous shocks prompt capital reallocation toward safer, ESG-aligned assets. Green bonds, underpinned by environmental commitments and long-term value orientations, have thus emerged as stabilizing instruments in periods of heightened uncertainty.

Collectively, these findings contribute to theoretical discourse by integrating perspectives from four complementary frameworks: Sustainable Finance Theory, Systemic Risk Theory, Institutional Theory, and Behavioral Finance. The convergence of empirical evidence across these frameworks underscores the value of a multidimensional analytical approach to understanding the systemic implications of green finance.

Policy and research implications follow directly. Policymakers should prioritize harmonizing ESG taxonomies, fostering deep and liquid green bond markets, and strengthening institutional capacity to maximize the benefits of systemic stability. Future research should examine contextual determinants of green finance effectiveness across diverse economic and institutional settings, thereby refining its role in enhancing global financial resilience.

To emphasize the novelty of the results of this study, the researcher displays the position of the research results and their differences with the results of previous research, as can be seen in the following table 9:

Study	Topic	Sample	Method	Key Findings	Gap Filled by This Study
Adrian & Brunnermeier (2016)	ΔCoVaR and systemic risk of banks	U.S. banks	Quantile regression	Identified risk interactions among banks	Did not address green instruments or cross-country panel analysis
Flammer (2021)	Green bonds and corporate performance	Global firms	Event study	Green bond issuance improves ESG performance	Did not assess macro-level systemic risk
Reboredo (2018)	Green bonds and financial markets	Global bonds	VAR	Relationship between green bond prices and energy markets	Did not analyze effects on ΔCoVaR
This study	Green bonds and cross-country systemic risk	30 countries, 2014–2023	Two-way FE with macro/market controls	Green bonds reduce ΔCoVaR; the effect is stronger in liquid markets and high-institution-quality countries	Provides multi-country panel causal evidence; tests institutional moderation; examines mediation via liquidity and investor composition

Table 9. *Research Position Map (Gap Map) vs. Previous Studies*

Heterogeneity Analysis

The heterogeneity analysis segmented the sample by market characteristics, distinguishing between developed and emerging economies and between high- and low-institutional-quality economies. Fixed-effects panel estimates reveal that the systemic risk reduction effects of green bond issuance are more pronounced and statistically significant in emerging economies and countries with high institutional quality. These results confirm that both institutional context and economic development level moderate the stability-enhancing impact of green bonds.

Mediation Analysis

To explore causal pathways, a formal mediation analysis was conducted with three mediators: market liquidity (LIQ), investor composition, and greenium (the premium on green bonds). Path analysis indicates that part of the effect of green bond issuance on reducing ΔCoVaR is mediated through improved market liquidity and a shift toward sustainability-oriented investor composition. Mediation via greenium was also detected, though its effect was smaller and statistically weaker. This suggests that green finance strengthens systemic stability both directly and indirectly by improving market conditions and investor behavior.

Placebo and Randomization Inference Tests

To ensure that the observed effects were not spurious, placebo tests were performed by randomizing the timing and treatment units of green bond issuance. Results from 1,000 randomization iterations produced coefficient distributions significantly different from the original estimates, reinforcing the causal interpretation of green bond issuance in reducing systemic risk.

Robustness Checks

Robustness was assessed through multiple approaches, consistent with best practices in high-impact empirical research. First, alternative model specifications were introduced that included lagged values of green bond issuance to address potential reverse causality and capture delayed effects. Variable transformations, including logarithmic forms, per capita measures, and GDP ratios, confirmed insensitivity to scaling. Different fixed-effects structures (country-only, time-only, and two-way) and alternative estimators (random effects and between estimators) were compared, with Hausman tests supporting the preferred specification.

Second, alternative estimation techniques were applied. Robust standard errors (Driscoll-Kraay, PCSE, and clustered standard errors) were used to address heteroskedasticity, autocorrelation, and cross-sectional dependence. Dynamic panel estimators (Arellano-Bond and system GMM) controlled for endogeneity and persistence in the dependent variable. An Instrumental Variable (IV) approach using renewable energy policy indices as instruments passed relevance and over-identification tests (Hansen/Sargan).

Third, subsample analyses examined temporal splits (pre- vs. post-COVID-19) and structural breaks following major regulatory reforms. Market-type splits (developed vs. emerging) and regional groupings further confirmed the consistency of results.

Fourth, alternative systemic risk measures (MES, SRISK, ΔCoVaR) yielded qualitatively consistent results.

Fifth, outlier and influence diagnostics (top/bottom 1% exclusion, Cook's distance, leverage statistics) showed that extreme values did not drive findings.

Sixth, diagnostic tests confirmed the absence of multicollinearity (VIF) and correct model specification (Ramsey RESET).

Journal of Studies in Academic, Humanities, Research and Innovation
Volume 3 No 1 June 2026
E-ISSN: 3089-7106
https://journal.as-salafiyah.id/index.php/sahri
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Seventh, temporal stability tests using rolling-window and recursive estimation confirmed the persistence of coefficient signs and magnitudes over time.

All robustness results are reported in supplementary tables, clearly labeled for direct comparison with baseline estimates. Any variations in coefficient behavior are documented and discussed for transparency.

Error Standard Validity

Comparisons of standard errors using Driscoll–Kraay, bootstrap, and wild cluster bootstrap methods yielded consistent significance levels, with minor differences in p-values. Driscoll–Kraay remains the preferred method, given its effectiveness in addressing heteroskedasticity, autocorrelation, and cross-sectional dependence in panel data of this size.

CONCLUSION

This study provides robust empirical evidence that green bond issuance is negatively associated with systemic financial risk across a diverse sample of 30 countries from 2014 to 2023. Using panel data econometrics and systemic risk measures (CoVaR), the analysis demonstrates that economies with more active and credible green bond markets tend to experience reduced systemic vulnerabilities. This relationship remains consistent even after controlling for macroeconomic conditions, market volatility, and liquidity. It is robust to various estimation strategies, including the use of lagged variables, instrumental variables, and subsample analyses.

The findings offer several significant contributions to the literature. First, the study extends the discourse on green finance by explicitly linking it to macro-financial stability, a previously underexplored area of research. Second, by incorporating both developed and emerging markets, the analysis captures a more comprehensive picture of how institutional contexts and market structures shape the risk-mitigating effects of green bonds. Third, the Indonesian case offers a nuanced understanding of how green finance can evolve in emerging economies, demonstrating promise while also underscoring the need for broader structural and regulatory reforms.

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Journal of Studies in Academic, Humanities, Research and Innovation
Volume 3 No 1 June 2026
E-ISSN: 3089-7106
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