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# Climate Risk in ESG Portfolios: Evidence from Indonesian Equity Markets

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**Abstract**

We examine whether ESG screening through the SRI-KEHATI index provides meaningful climate risk isolation compared to the IHSG market index. Using 1,499 daily observations from January 2013 to December 2025, we apply Least Absolute Shrinkage and Selection Operator (LASSO) as a dimensionality reduction step from 50 candidate predictors, followed by a Quantile Regression Neural Network (QRNN) to estimate dynamic Value-at-Risk (VaR) at three quantile levels (99%, 95%, 90%), and SHAP (SHapley Additive exPlanations) for variable attribution. LASSO eliminates all climate variables across all specifications. Partial correlation analysis reveals the mechanism: once domestic equity factors are controlled, the raw correlation of clean-energy returns with IHSG collapses from 0.121 to −0.0005, confirming complete mediation. Climate contributions rise from 6.12% at VaR 90% to 17.25% at VaR 99% (ratio 2.82), indicating that stress tests anchored at VaR 95% systematically understate tail climate exposure. QRNN outperforms Historical Simulation VaR and GARCH(1,1)-$t$ across all 12 Diebold-Mariano comparisons ($p < 0.001$).

**Keywords:** climate risk; dynamic VaR; ESG; LASSO; quantile regression neural network

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## 1. Introduction

Indonesia ranks among the countries most exposed to climate risk globally. Between 2013 and 2025, climate-related disasters caused losses exceeding any previous decade on record: the 2019 peatland fires cost roughly 0.5% of GDP [1], the 2020 Jakarta floods killed 173 people and caused Rp 1 trillion in infrastructure damage [2], and the November 2025 Sumatera floods resulted in losses of Rp 68.67 trillion. The Indonesia Stock Exchange (IDX) listed more than 900 companies by 2025, with daily turnover routinely exceeding Rp 10 trillion.

The SRI-KEHATI index, managed by the Indonesian Biodiversity Foundation, is Indonesia's primary Environmental, Social, and Governance (ESG) investment proxy, selecting 25 issuers based on strict sustainability criteria. ESG screening should theoretically reduce climate risk exposure. The empirical question has not been answered: does ESG screening genuinely protect against climate risk in the distributional tail, and if so, through what mechanism?

We address both questions through a three-stage pipeline: (1) LASSO for dimensionality reduction from 50 candidate predictors, (2) QRNN for dynamic VaR estimation, and (3) SHAP for variable contribution attribution. We analyze 1,499 daily observations (September 2014–December 2025) for SRI-KEHATI and IHSG as the broad-market comparator. The results run

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in three directions. LASSO eliminates all climate variables because domestic equity factors fully mediate their signals: the clean-energy return correlation with IHSG collapses from 0.121 to −0.0005 in partial correlation. Climate contributions are tail-concentrated, rising 2.82-fold from VaR 90% to VaR 99%. QRNN consistently outperforms conventional models in 12 Diebold-Mariano comparisons. This is the first quantitative evidence of domestic market mediation of climate signals in an ASEAN ESG portfolio, consistent with Green Swan theory [3], though no prior study has measured this at daily resolution for an emerging market.

### 1.1. ESG Investing and Tail Risk

The literature on ESG portfolio performance is extensive but inconclusive at the mean-return level [4]. At the tail risk level, findings are more consistent. Engle et al. [5] show that ESG factors hedge against negative climate news in U.S. equity markets, though hedge ratios are time-varying and small in magnitude. Lashkaripour [6] documents that tail risk in high-ESG stocks rises 14% more than low-ESG stocks during market crashes. For Indonesian markets, Yasya et al. [7] compare SRI-KEHATI with IHSG on return characteristics but do not examine climate risk exposure at the distributional tail; this study fills that gap.

### 1.2. Climate Risk in Financial Markets

Bolton et al. [3] characterize climate risk as Green Swan events: tail risks highly probable in the long run but difficult to price under conventional distributional assumptions. Barnett, Brock, and Hansen [8] show that climate uncertainty commands a risk premium concentrated in the tail of the asset return distribution. Faccini, Matin, and Skiadopoulos [9] find U.S. equity markets respond significantly to climate news shocks at monthly frequency. Caldara and Iacoviello [10] provide the Geopolitical Risk Daily Index used as a climate-adjacent predictor. For ASEAN emerging markets, evidence on climate risk pricing in ESG portfolios remains sparse, and this paper addresses that gap directly.

### 1.3. Dynamic VaR Methods and Machine Learning

VaR estimation has shifted from parametric approaches toward semiparametric and nonparametric methods as empirical evidence of fat tails has grown. QRNN, first proposed by Taylor [11], estimates conditional quantiles without distributional assumptions by optimizing the pinball loss function. Liu and Luger [12] document that quantile-based semiparametric models outperform GARCH for tail risk forecasting. For high-dimensional variable selection, LASSO [13] is now widely used. Belloni and Chernozhukov [14] establish that the two-step approach (LASSO-OLS for selection, quantile estimation separately) is asymptotically consistent. Lundberg and Lee [15] propose SHAP for decomposing individual predictions into variable-level contributions using cooperative game theory. Awijen, Ben Jabeur, and Pillot [16] apply SHAP to decompose ESG factor contributions to stock prices with climate control variables.

## 2. Methods

### 2.1. Data

The panel covers 1,499 trading days from September 2014 to December 2025, effective after listwise deletion from 3,146 raw observations spanning January 2013 to December 2025. Two target variables are the log daily returns of SRI-KEHATI and IHSG. Table 1 summarizes 50 predictor variables across seven categories covering global equity markets, commodities, exchange rates, domestic macro, domestic equity markets, internal index factors, and climate and ESG indicators. Two data quality corrections are documented explicitly. First, the BI Policy Rate was excluded from the predictor set due to frequency mismatch: as a monthly-determined variable, its daily forward-filled values lack within-month variation and are theoretically inappropriate as

predictors in a daily return model. Second, CPO futures trade on Bursa Malaysia Derivatives, which observes different public holidays from IDX; this 141-day calendar mismatch generated artificial return spikes (SD 3.46% before correction), resolved by forward-filling CPO closing prices before computing log returns, reducing SD to 1.46%.

**Table 1:** Variable categories and counts.

| Category | N | Representative Variables |
|---|---|---|
| Global Markets | 10 | S&P 500, DJIA, Nasdaq, MSCI EM, Nikkei, Hang Seng, FTSE 100, DAX, VIX, Shanghai |
| Commodities | 10 | WTI, Brent, CPO, coal, gold, silver, copper, nickel, tin, aluminum |
| Exchange Rates | 4 | USD/IDR, EUR/IDR, JPY/IDR, CNY/IDR |
| Domestic Macro | 4 | SBN 10Y & 5Y yields, UST 10Y, CDS Indonesia 5Y |
| Domestic Markets | 7 | LQ45, JK Finance, ISSI, JK Mining, MSCI Indonesia, ESG Global, Bitcoin |
| Internal Index Factors | 9 | Lagged return, daily volume, 22-day realized volatility (per index) |
| Climate & ESG | 8 | Physical Risk Index, Transition Risk Index, GPR Daily [10], ERA5 temperature anomaly, CHIRPS rainfall, carbon EUA return, natural gas return, clean energy equity return |

All predictor variables enter the model as end-of-day conditioning information available at time $t$, consistent with the end-of-day conditional risk measurement framework [17]. After listwise deletion, the effective estimation sample contains 1,499 observations, split 80/20 chronologically: 1,199 training observations through October 2023 and 300 test observations from November 2023 through December 2025.

## 2.2. LASSO Variable Selection

LASSO [13] is implemented via the `glmnet` package in R as a dimensionality reduction step prior to QRNN estimation. With 50 candidate predictors and an effective sample of 1,499 observations, fitting QRNN directly risks severe overfitting; LASSO reduces the input dimension to a manageable subset while retaining variables with meaningful conditional association. In an end-of-day conditional framework, selected variables reflect contemporaneous market co-movement rather than predictive causation; LASSO functions as dimensionality reduction to prevent QRNN overfitting, not as identification of causal risk determinants. Three variables enter without penalty (lagged return, 22-day realized volatility, daily volume) to retain basic autoregressive structure. The penalty parameter $\lambda$ is selected by five-fold expanding-window cross-validation, where each fold trains on the expanding historical window and validates on the next block to preserve temporal order. As a robustness check, three LASSO-QR variants using `rqPen` were tested; all produced non-sparse models ($\lambda$ approaching zero), confirming LASSO-OLS two-step as the more empirically stable approach [14].

## 2.3. Quantile Regression Neural Network (QRNN)

The QRNN architecture follows Taylor [11] with modifications for high-dimensional financial data. The network structure is: Input $\rightarrow$ Linear(64) $\rightarrow$ BatchNorm $\rightarrow$ ReLU $\rightarrow$ Dropout(0.2) $\rightarrow$ Linear(32) $\rightarrow$ BatchNorm $\rightarrow$ ReLU $\rightarrow$ Dropout(0.2) $\rightarrow$ Linear(3). The output layer produces simultaneous estimates for $\tau \in \{0.01, 0.05, 0.10\}$. The loss function is the aggregate pinball loss:

$$L(y, \hat{q}, \tau) = \frac{1}{N} \sum_{i=1}^{N} \max[\tau(y_i - \hat{q}_i),\ (\tau - 1)(y_i - \hat{q}_i)] \tag{1}$$

Rolling-window predictions introduce distributional shift because return scale varies across windows. We z-score normalize the target variable within each 250-day training window and initialize the output layer bias from the empirical quantile of that window (warm-start bias). Without this adjustment, BatchNorm produces divergent predictions across windows due to the mismatch between running statistics and the local distribution.

### 2.4. SHAP Attribution and Backtesting

KernelSHAP [15] is applied with 100 background observations per training window. The climate contribution per observation is defined as:

$$\text{Climate_SHAP}(t) = \frac{\sum_{j \in \mathcal{C}} |\phi_j(t)|}{\sum_{\text{all } j} |\phi_j(t)|} \times 100\% \tag{2}$$

where $\phi_j(t)$ is the SHAP value of variable $j$ at observation $t$, and $\mathcal{C}$ denotes the set of climate variables. Computing the ratio per observation and then averaging avoids the bias that arises when observations with large total SHAP magnitude dominate the aggregate. Backtesting uses three complementary procedures: the Kupiec [18] test for violation frequency, the Christoffersen [19] test for temporal clustering of violations, and the Dynamic Quantile (DQ) test of Engle and Manganelli [20] for violation predictability. Comparative accuracy uses the Diebold-Mariano test [21] with Newey-West HAC standard errors evaluated on pinball loss. Two benchmarks are Historical Simulation VaR (empirical quantile of the 250-day rolling window) and GARCH(1,1)-$t$ [22], both refitted monthly.

## 3. Results and Discussion

### 3.1. Distributional Properties

Table 2 reports distributional statistics for both return series. SRI-KEHATI shows excess kurtosis of 9.21, versus 7.75 for IHSG, and both series reject normality overwhelmingly (Jarque-Bera $p < 0.001$). A normal distribution underestimates VaR 99% by 18.5% for SRI-KEHATI and 21.8% for IHSG, meaning that risk models built on normality will systematically miss the losses that matter most. This concentration effect is consistent with the SRI-KEHATI portfolio containing only 25 constituents versus 900+ in IHSG: idiosyncratic shocks not diversified away in the smaller portfolio produce index-level extremes more frequently. Fig. 1 displays the empirical return distributions; the pronounced left tail confirms the inadequacy of the normal benchmark at the VaR 99% level.

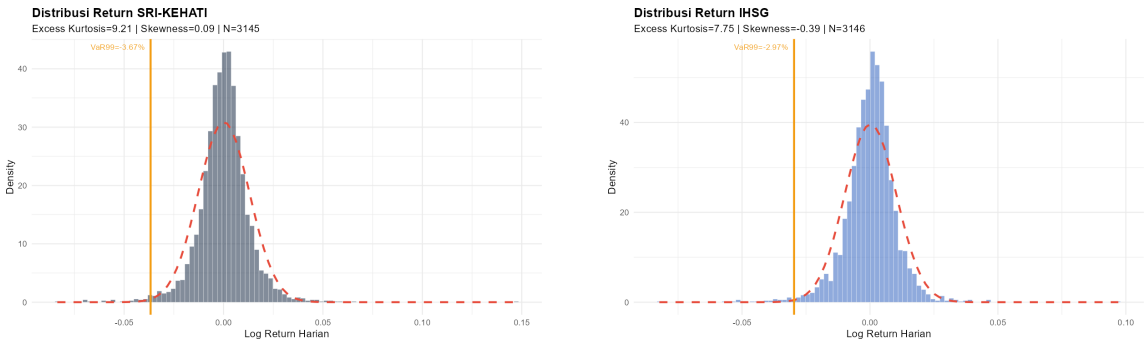
### 3.2. LASSO Feature Selection Results

Table 3 reports LASSO-retained variables across indices and quantile levels. For SRI-KEHATI, three domestic BEI market variables dominate: LQ45, JK Finance sector, and ISSI Islamic equity index; all three trade on the same exchange with identical closing times as SRI-KEHATI, so their selection reflects contemporaneous co-movement rather than predictive causation. For IHSG, a perfectly nested pattern emerges: the variable set at $\tau = 0.01$ is a strict subset of $\tau = 0.05$, which is a subset of $\tau = 0.10$, meaning that global market variables (Nikkei, Hang Seng, gold) enter only at lower quantile extremity. No climate variable enters any specification across both indices. Fig. 2 traces the LASSO regularization paths; the horizontal trajectories of climate variables across the full $\lambda$ range confirm that elimination is not a boundary artifact of the chosen $\lambda$ but a consistent pattern across all regularization levels.

**Table 2:** Distributional statistics for SRI-KEHATI and IHSG daily log returns, January 2013–December 2025.

| Statistic | SRI-KEHATI | IHSG |
|---|---|---|
| Observations | 3,145 | 3,146 |
| Mean (% per day) | 0.016 | 0.022 |
| Standard deviation (%) | 1.292 | 1.006 |
| Minimum (%) | −8.36 | −8.23 |
| Maximum (%) | +14.73 | +9.70 |
| Skewness | 0.09 | −0.39 |
| Excess kurtosis | **9.21** | **7.75** |
| Historical VaR 99% (%) | **−3.67** | **−2.97** |
| Parametric normal VaR 99% (%) | −2.99 | −2.32 |
| Normal model underestimate (%) | 18.5 | 21.8 |

*Note.* Jarque-Bera rejects normality for both series at $p < 0.001$.




**(a)** SRI-KEHATI. **(b)** IHSG.

**Fig. 1:** Return distributions for (a) SRI-KEHATI and (b) IHSG daily log returns, January 2013–December 2025. The shaded area represents the fitted normal distribution. Excess kurtosis of 9.21 (SRI-KEHATI) and 7.75 (IHSG) confirms distributional fat tails that normal models systematically understate.

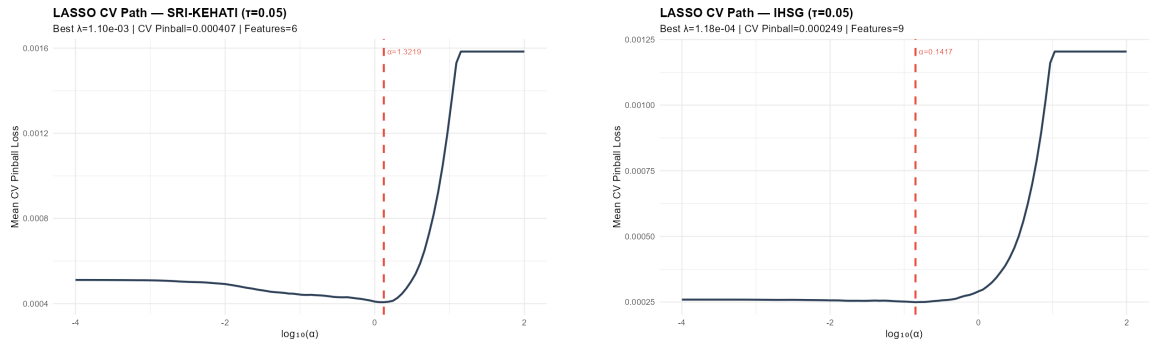
**Table 3:** LASSO-retained variables by index and quantile level.

| Index | $\tau$ | Selected Variables (excl. unpenalized terms) |
|---|---|---|
| SRI-KEHATI | 0.01 | `lq45_ret, jk_finance_ret` |
| SRI-KEHATI | 0.05–0.10 | `lq45_ret, jk_finance_ret, issi_ret` |
| IHSG | 0.01 | `cds_id_5y, lq45_ret, jk_finance_ret, issi_ret, jk_mining_ret` |
| IHSG | 0.05 | Previous set + `nikkei_ret` |
| IHSG | 0.10 | Previous set + `hang_seng_ret, gold_ret` |
| **Both indices** | **All $\tau$** | **No climate variable selected** |

*Note.* Unpenalized terms (forced): 1-day lagged return, 22-day realized volatility, daily volume proxy.

### 3.3. Climate Risk Elimination Mechanism: Full Mediation

Table 4 shows why climate variables are eliminated. The raw correlation of `clean_energy_ret` with IHSG is 0.121, substantial enough to imply a meaningful relationship. After six domestic equity and volatility controls enter the partial correlation model, the coefficient collapses to −0.0005, consistent with complete mediation [23]: domestic equity factors absorb the entire predictive signal from climate variables before those variables can contribute independently to the model. This pattern holds across six of the eight climate variables. One exception is the Geopolitical Risk Daily index [10], whose partial correlation (0.042) exceeds its raw correlation (0.012), a suppressor effect indicating that domestic factors previously concealed the GPR signal rather than absorbing it.




**(a)** SRI-KEHATI. **(b)** IHSG.

**Fig. 2:** LASSO regularization paths for (a) SRI-KEHATI and (b) IHSG. Each line represents one predictor variable's coefficient trajectory as $\lambda$ decreases. Climate variables remain flat at zero across the full $\lambda$ range, confirming that their elimination is not a boundary artifact.

**Table 4:** Raw and partial correlations of climate variables with IHSG daily returns.

| Variable | Raw | Partial | Interpretation |
|---|---|---|---|
| `clean_energy_ret` | 0.121 | **−0.0005** | Complete mediation |
| `carbon_eua_ret` | 0.035 | −0.0003 | Complete mediation |
| `chirps_rainfall` | 0.027 | 0.002 | Complete mediation |
| `era5_temp_anomaly` | −0.009 | −0.008 | Complete mediation |
| `gpr_daily` | 0.012 | **0.042** | Suppressor effect |
| `pri, tri, nat_gas` | <0.03 | 0.02–0.03 | Weak throughout |

*Note.* Control variables: `lq45_ret`, `jk_finance_ret`, `issi_ret`, `jk_mining_ret`, `rv_ihsg_22`, `ihsg_lag1`.

### 3.4. SHAP Attribution and Tail-Concentrated Climate Risk

Table 5 reports aggregate SHAP climate contributions for three model variants. In the main QRNN models, climate SHAP is zero by construction because no climate variable enters the feature set. When climate variables are forced into a diagnostic QRNN (IHSG+Climate), their combined SHAP share is 11.1% at $\tau = 0.01$, the primary estimate of climate contribution under the QRNN framework. The forced inclusion is theoretically motivated: LASSO eliminates climate variables because their marginal predictive contribution is absorbed by domestic factors [9], not because they are economically irrelevant [23]. The three largest climate contributors are CHIRPS rainfall (55.5% of total climate SHAP), GPR Daily (24.6%), and carbon EUA returns (20.0%). Fig. 3 presents the SHAP feature importance and time-varying contribution analysis. Physical climate indicators contribute more than transition risk indicators, suggesting that acute physical shocks are more visible at the daily tail frequency than the slower-moving transition channel.

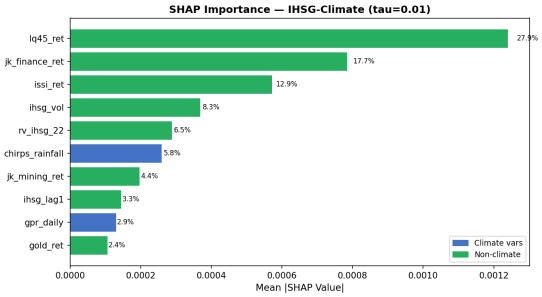
**Table 5:** SHAP climate contribution by model and quantile level (%).

| Model | $\tau$=0.01 | $\tau$=0.05 | $\tau$=0.10 | Method |
|---|---|---|---|---|
| QRNN Main (SRI-KEHATI) | 0.00 | 0.00 | 0.00 | Natural |
| QRNN Main (IHSG) | 0.00 | 0.00 | 0.00 | Natural |
| QRNN+Climate (IHSG) | **11.10** | 11.46 | 9.05 | Forced |
| Diagnostic LASSO-QR | **17.25** | 8.40 | 6.12 | Diagnostic |

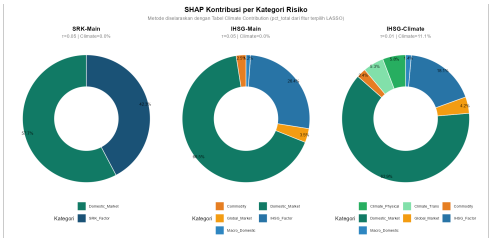
*Note.* SHAP computed per observation and averaged. Diagnostic LASSO-QR uses separate quantile regression; not directly comparable to QRNN rows.

Climate contributions rise from 6.12% at $\tau = 0.10$ to 17.25% at $\tau = 0.01$ in the diagnostic model, a ratio of 2.82 between VaR 99% and VaR 90% levels. The time-varying SHAP in Fig. 3(c) tracks this contribution across the 300-day test period; climate contribution is persistent

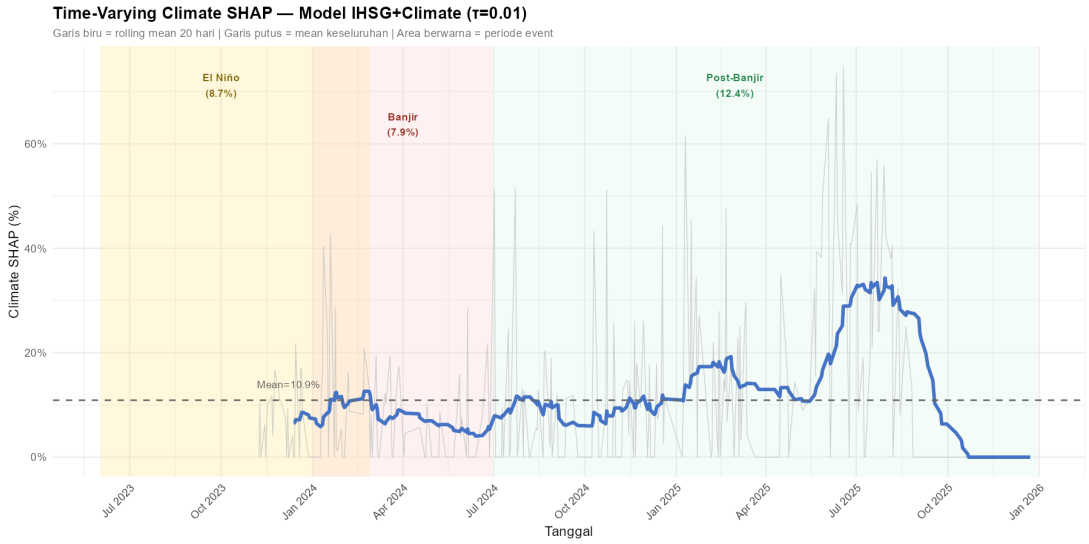
(averaging 8–12% throughout) rather than episodic. The absence of pronounced spikes during marked climate events (El Niño 2023, Flood 2024) suggests that climate risk is continuously embedded in market pricing through the domestic factor channel, becoming visible only when that channel is explicitly removed. OJK Regulation No. 51/POJK.03/2017 requires climate risk disclosure without specifying a VaR confidence level; regulators using VaR 95% as a climate stress benchmark capture approximately half the tail exposure visible at VaR 99%.




**(a)** SHAP feature importance ($\tau = 0.01$).




**(b)** SHAP by risk category (three variants).




**(c)** Time-varying climate SHAP, November 2023–December 2025.

**Fig. 3:** SHAP attribution for QRNN+Climate (IHSG, $\tau = 0.01$). (a) Mean absolute SHAP values by variable; climate variables form a measurable second tier dominated by CHIRPS rainfall (5.8%) and GPR Daily (2.9%). (b) SHAP contribution by risk category across three model variants; the climate slice (blue/teal) appears only in the forced-inclusion panel, confirming domestic factors absorb the climate signal in main specifications. (c) Time-varying climate SHAP; shaded regions mark El Niño 2023 (8.7%), Flood 2024 (7.9%), and Post-Flood 2025 (12.4%). Period averages do not differ significantly (Mann-Whitney $p = 0.41$), indicating persistent rather than episodic climate contribution.

## 3.5. Backtesting and Benchmark Comparison

Table 6 reports backtesting results for the main QRNN models. QRNN passes all three criteria for SRI-KEHATI at all quantile levels. For IHSG at $\tau = 0.05$, the Kupiec test fails with a violation rate of 2.0% against the expected 5.0%; this under-violation indicates the model is overly conservative for the test period, not under-fitted, as a conservative model errs toward greater capital protection relative to the regulatory benchmark. The Dynamic Quantile Test passes in all nine configurations ($p = 0.425$–$0.934$), confirming that violations are serially uncorrelated and unpredictable from lagged information. QRNN wins all 12 Diebold-Mariano comparisons against both benchmarks (all $p < 0.001$) with pinball loss improvement factors of 2.0–2.6×, demonstrating that the accuracy advantage is statistically robust and not driven by a single

quantile or index.

**Table 6:** Backtesting results and Diebold-Mariano statistics, main QRNN models (test set $N = 300$, November 2023–December 2025).

| Index | $\tau$ | Viol. Rate | Kupiec $p$ | DM vs HS-VaR | DM vs GARCH-$t$ |
|---|---|---|---|---|---|
| SRK | 0.01 | 0.33% | 0.178 | $4.31^{***}$ | $7.24^{***}$ |
| SRK | 0.05 | 3.67% | 0.267 | $6.43^{***}$ | $6.93^{***}$ |
| SRK | 0.10 | 7.00% | 0.069 | $7.23^{***}$ | $8.17^{***}$ |
| IHSG | 0.01 | 0.33% | 0.178 | $3.44^{***}$ | $4.08^{***}$ |
| IHSG | 0.05 | 2.00%* | 0.007 | $6.06^{***}$ | $6.05^{***}$ |
| IHSG | 0.10 | 7.33% | 0.108 | $6.73^{***}$ | $7.37^{***}$ |

$^{***}p < 0.001$. *Kupiec fails (under-violation: model over-conservative, not under-fitted).
Positive DM statistic = QRNN achieves lower pinball loss. DQ test: 9/9 PASS ($p = 0.425$–$0.934$).

## 4. Conclusion

We tested whether ESG screening through the SRI-KEHATI index isolates portfolio tail risk from climate exposure, using a three-stage LASSO-QRNN-SHAP pipeline on 1,499 daily observations. Three results stand out. First, LASSO eliminates all climate variables not because climate is irrelevant, but because domestic equity factors fully mediate climate signals: the `clean_energy_ret`–IHSG correlation collapses from 0.121 to −0.0005 in partial correlation, confirming that climate risk enters markets through domestic asset prices, which incorporate it faster than daily-frequency models can detect as a separate channel. Second, climate contributions are tail-concentrated, rising 2.82-fold from VaR 90% to VaR 99%; OJK Regulation No. 51/POJK.03/2017 requires climate risk disclosure without specifying a VaR confidence level, and our results provide empirical grounds for specifying VaR 99% as the minimum threshold in future regulatory guidance. Third, QRNN outperforms both Historical Simulation VaR and GARCH(1,1)-$t$ across all 12 Diebold-Mariano comparisons (all $p < 0.001$) with pinball loss 2.0–2.6× lower. Limitations include the 52.4% sample reduction from listwise deletion (though results are robust to the alternative specification in Appendix A), the end-of-day conditioning framework that limits interpretation to risk attribution rather than pure forecasting, and the single-country, single-index scope. Replication in Malaysia (FTSE4Good Bursa Malaysia), Thailand (SET ESG), and other ASEAN markets would establish whether the mediation mechanism is regional or specific to Indonesia.

## CRediT Authorship Contribution Statement

**Annisa Syalsabila:** Conceptualization; Methodology (hybrid LASSO-QRNN architecture design); Software (model development and tuning); Formal Analysis; Investigation; Writing – Original Draft; Writing – Review & Editing; Visualization; Project Administration; Funding Acquisition; Supervision. **Nur Ikhwana:** Data Curation (acquisition from Nasdaq, Investing.com, Yahoo Finance, and other sources; frequency harmonization; feature engineering); Formal Analysis (SHAP interpretation); Writing – Review & Editing. **Lalu Ramzy Rahmanda:** Data Curation; Formal Analysis (exploratory analysis and diagnostic testing); Validation (Kupiec, Christoffersen, and Dynamic Quantile backtesting); Writing – Review & Editing.

## Declaration of Generative AI and AI-assisted Technologies

The authors used Claude (Anthropic) during manuscript preparation for the following purposes: writing assistance (drafting and editing prose sections). The authors take full responsibility for the integrity of this work.

## Declaration of Competing Interest

The author declares no competing interests.

## Ethics Approval and Consent to Participate

Ethics approval was not required for this study. All data used are publicly available from financial data providers and open-access climate databases.

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## Data and Code Availability

The panel dataset and R/Python analysis scripts are available from the author upon reasonable request. Climate data are publicly available from the Copernicus Climate Data Store (https://cds.climate.copernicus.eu) and UCSB CHIRPS (https://www.chc.ucsb.edu/data/chirps). Financial data are sourced from Yahoo Finance and Investing.com.

## A. Sensitivity Check Results

When CPO futures, Bitcoin, aluminum, and late-starting FX variables are excluded prior to listwise deletion, the effective sample increases from 1,499 to 2,847 observations (90.5% of total), covering the full period from January 2013 to December 2025. LASSO selects an identical feature set for SRI-KEHATI and a structurally equivalent nested feature set for IHSG. QRNN backtesting passes 11 of 12 configurations, matching the main result. All 12 Diebold-Mariano statistics remain significant at $p < 0.001$. These results confirm that the sample reduction in the main analysis does not introduce systematic bias and that the findings are robust to the choice of predictor set.

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