The implication of the Yield Volatility of the Green Bond Markets versus Arab Insurance Investment Portfolios under Geopolitical Uncertainty: Networking and Artificial Intelligence.
(A study of some markets in the Gulf Cooperation Council (GCC) countries and North Africa)

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Abstract

Aim of the study is explored the linkage between the yield volatility for global green bonds and Arab insurance investments around key moments of large geopolitical friction. Moving away from a theory of portfolio diversification as always being the most efficient, the

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model will explicitly quantify when interdependencies break or when they are restored in times of stress.
Methodology, Design and Approach of the study : In order to avoid the constraints of infrequent issuance of high frequency disclosures in the Arab insurance market, we used a representative portfolio of known ETFs and proxy indices. It guarantees exposure to fixed income, green bonds, equity, and cash markets. The dataset has daily data from January 2020 to December 2024, which includes both times from the dataset.
The study uses the Diebold-Yilmaz index that is included into a Time-Varying VAR (TVP-VAR) model for volatility spillover estimation. We model geopolitical instability by the Caldara-Iacoviello GPR index and its role as both external determinant and a threshold for the potential regime change. The predictive effectiveness of the analysis is then compared to estimates based on GARCH (1,1) and DCC-GARCH, as well as using LSTM networks.
Results of the study It explains (1)The effect of volatility is strong, asymmetric, and time-varying; green bonds behave as net remittances and insurance portfolios as net recipients. (2) The total flow index almost doubles in these scenarios of high geopolitical risk (31.4% → 58.9%), and it indicates that the benefits generated by diversification decay with a rise in systemic stress. (3) LSTM networks reduce RMSE out of sample by 32%, better than GARCH, with a statistically significant improvement (Diebold-Mariano test, $p<0.01$). (4) Scenario-based forecasts show that insurance portfolio volatility is disproportionately sensitive to negative geopolitical escalations.
Recommended The researchers that academics should be called upon to make efforts to develop systemic risk management tools.
Keywords – Green Bonds, Arab Insurance Companies, Vulnerability Impacts, Networking, Geopolitical Risks, Artificial Intelligence, LSTM.

1. Introduction

1.1 Background and motivation

On a more macro level, international markets have experienced concurrent instabilities arising from armed conflicts, ecological shocks, in combination with a rapid transition to a more sustainable capital allocation starting from 2020. The green finance of initiatives relied heavily on green bonds, which had a total over US$2.5 trillion market value as of year-end 2024 (Climate Bond Initiative, 2024). This is being paired with emerging funding from institutional investors, including insurers, that consider returns key to limiting long-term liabilities and responding to changing mandates for sustainable finance. The post-2020 period, for the researcher, is a structural interruption of market correlations. Traditional diversification strategies could wane; therefore, green bonds on high-commitment portfolios may no longer matter today for conventional diversification strategies and they should be revisited with a view to contagion risk. Insurance in the Arab world insurance market is transforming quickly. GCC institutions are becoming more intertwined with overseas capital markets while North African partners are largely localist and conservative when it comes to investment. Yet adopting green instruments is routine. Take, for instance, the leading insurers in KSA and the UAE who have embraced net-zero rules and growing demand for green bonds dating from 2021. However, the impact on the stability of these portfolios has yet to be seen. The researcher asserts that a severe shortfall in the availability of data has seriously compromised the ability of Arab regulatory authorities to monitor international risk spillovers effectively. Through an agent-based industry portfolio, the author has succeeded in plugging this gap and forms objective benchmarks with characteristics that can be transposed to other emerging financial markets. Novelty/Value — This study is the first of its kind in providing (a) an agent-based insurance portfolio specifically for the Arab region, focusing on green bond implications; (b) integration of the Diebold-Yilmaz network analytical analysis with sustainable finance management under the geopolitical transformation of regulation; and (c) actionable policy implications for sustainable finance and insurance supervision relevant when operating in emerging markets.

1.2 Problem Statement

Volatility spillovers represent the spread of uncertainty shocks, and thus are one of the essential channels through which systemic risk is transmitted. Fewer hedge instruments will be accessible, which will make it more difficult for portfolios to adjust; asset classes in particular move together when a geopolitical crisis strikes. For insurance companies functioning under Solvency-style regulatory regimes in the Arab region, such sudden surges in volatility tend to cause liquidity pressures, forced asset liquidations, and additional market destabilization. While the connection between green and traditional assets is well documented, the researcher calls attention to the fact that insurance portfolios—with their specialized liability constraints and regulatory oversight—have been left out of academic discourse. The study does sufficiently cover this gap and adds these idiosyncratic institutional features into the picture.

1.3 Research Questions and Contributions

There are three main goals that guide our analysis:

Q1: Quantifying the intensity and trajectory of yield volatility among global green bond sectors and Arab insurance holdings.

Q2: Studying geopolitical risk as a threshold variable that governs these relationships during stressed and stable regimes.

Q3: Examining the incremental value of LSTM in improving the predictive precision for insurance risk:

1. First, the development of an agent-based industrial insurance portfolio for five key Arab markets enabling high-frequency systemic risk analysis.
2. The integration of the Diebold-Yilmaz network interconnection with the shifting geopolitical systems, revealing the dynamics of state-dependent extension.
3. Comparison of LSTM vs. GARCH in a new context (Arab Insurance + Green Bonds), with accurate statistical verification.
4. Providing scenario-based volatility forecasts (baseline, medium risk, elevated risk) that can be used directly by regulators and risk managers.

1.4 Sheet Structure

The second part provides literature review and critique of integrated researchers and future work. Section 3 presents the synthetic portfolio, data sources, and the geopolitical risk measurement. This is the integrated methodological framework (econometrics, networking, artificial intelligence) in Section IV. Experimental results are presented in Section 5, with tables, graphs, and algorithmic summaries. Theoretical and practical implications are addressed in Section 6. The department conducts seven durability checks. Section 8 of this paper describes limitations and future research directions. Article 9 ends with policy proposals. Futurist View of the Future: Our future research will also need to make an expanded agent-based portfolio in particular focus on liability side dynamics (such as claims shocks and longevity risks) and see if effects of green bonds will be particularly strong for ESG-rating insurers. Furthermore, satellite-based measures of geopolitical tension (e.g., data collected on the site of armed conflict) could enhance the measurement of ‘local’ geopolitical risks.

2. Review the literature

2.1 Green bonds and financial market volatility

Even though early studies tended to converge on the link between green bonds’ performance and that of traditional debt instruments, this consensus is diminishing. Other studies find that the volatility profile and connection to the market for green assets diverge significantly when we go beyond benign market environments. This is a more conditional nature of risk and has potentially led to a conclusion that green bonds may not be reliable safe havens in times of substantial geopolitical or financial distress. Emerging empirical evidence shows that the risk behavior of green bonds is also regime-dependent and it calls into question the assumption that green bonds act as perpetual safe havens in times of financial distress. The investigator suggests that the changing dynamics of green bonds—from being a niche ESG project to a mainstream asset class—suggests that they have dynamic risk features by nature. Thus, researchers need to transcend static correlation equations and apply more regime-switching (or time-varying) models. This methodological necessity is directly addressed in this study. Another research void is how green assets are affecting insurance-based institutional portfolios. The long-term durations and capital adequacy requirements of insurance firms are likely to induce the spillover dynamics in unique patterns that require further research (Perth et al., 2022).

On the other hand, these bonds are highly sensitive to financial market volatility, including changes in interest rates, inflation, and global economic and political fluctuations. This volatility leads to increased risks for investors, but it can also offer opportunities for higher returns if managed strategically. Recent research seeks to understand the relationship between the performance of green bonds and the movements of financial markets, contributing to the development of risk management tools and improved sustainable investment strategies. Green bonds are also an innovative financial instrument designed to fund environmentally friendly and sustainable projects, such as renewable energy and natural resource management. This financial instrument has seen remarkable growth over the past decade as a result of increased interest in sustainability and corporate and governmental social responsibility. (Vihervuori,2023)

2.2 Insurance Investment Portfolios and Regulatory Risks

Long-term commitments form the structural part of insurance balance sheets – the institutional portfolio profile. As a rule, it is not the traditional view of these entities as conservative actors, but it’s a misdirection in a crisis; rather than absorbing shocks, a gap in assets/liabilities increases systemic volatility. This disparity is particularly concerning in emerging jurisdictions that impose stricter regulations that constrain the complicated hedging tools that are made available to the public. Systemic Fragility: Lessons from the 2008 financial crisis and the 2020 COVID-19 market downturn help explain why insurers are at risk of a double-sided squeeze on the balance sheet: low asset values and bloated liabilities are the co-factors behind a low-rate environment. (Perth et al., 2022).

On the other hand, these portfolios face regulatory risks stemming from changes in financial laws and regulations that affect investment policies and required capital reserves. These risks include compliance requirements, investment restrictions, and solvency standards imposed by regulatory bodies. Effectively managing these risks is essential to maintaining the sustainability of insurance companies and protecting the interests of stakeholders. Recent studies also highlight the importance of integrating regulatory risk assessment into insurance investment strategies to ensure a balance of returns while minimizing exposure to market and regulatory risks. (Susac,2022)

highlight that as the duration mismatch between insurers' duration and market liquidity increases in a constrained market liquidity environment, its contribution to more widespread disorder grows. The author contends that while the uniformity in the regional blocs is remarkable, the Arab insurance markets face systemic imperfections in specific aspects, such as hedging and sovereign debt bias. The shift to green bonds brings currency-related risks – the products are often not backed by local currency – and local portfolios are therefore connected to the global contagion routes. Significant Shortcomings: As attention on green bond volatility rises, less attention has been given to the impact of green bond volatility on insurance-linked portfolios in emerging regions. Our study presents the first specific evaluation of these financial links. (Said et al., 2023)

2.3 Network interdependence and the Diebold–Yilmaz framework Context: While Diebold–Yilmaz is among the fundamental frameworks for the analysis of spillover dynamics in traditional markets, the inclusion of the Diebold–Yilmaz concept into the analysis of the insurance sector is relatively underserved. Since insurance companies are subject to tailor-made liability regimes and solvency-centric guidelines, ignoring this industry in connectedness research neglects the crucial aspect of systemic risk. Applications. This method has been utilized for commodities, cryptocurrencies, and sovereign bonds. Recent business has involved climate-related risks (Said et al., 2023) and geopolitical shocks (Puri et al., 2023). Networking is more than a mere statistical exercise; it exposes the 'plumbing' of the financial system. Now, our study applies them to finding green linkages to function as a systemic node during geopolitical strains, which we identify as significant, with clear precautionary implications. Gaps. Insurance investment portfolio networks hardly get any analysis.

2.4 Geopolitical Risks and Financial Markets

Measurement. Caldara and Yacovello (2022) developed the GPR through automated text mining in newspapers, documenting war, terrorism, and political tensions. It has become the standard agent.

Experimental regularities. A higher cash income rate is associated with lower equity returns, higher volatility, and increased interconnectedness between markets (Buri et al., 2023). The impact is stronger in emerging markets.

In the context of the Arab region, geopolitical risk should not be treated as an episodic disturbance. Instead, it represents a persistent structural condition that repeatedly reshapes financial linkages. Modeling such risk as a simple dummy variable risks understating its systemic role, particularly during prolonged periods of political tension.

Gaps. GPR has not been linked to the effects of green bonds – insurance.

2.5 Artificial Intelligence in Predicting Volatility

Deep learning in the area of finance. Although emerging literature indicates that LSTM models have a better forecast performance in comparison to typical GARCH specifications, such better forecasting results should not be considered automatic or universal. Successful incorporation of these techniques into deep learning depends on efficient feature extraction and training routines that are provided by extensive historical crises with deep data-rich epochs, and robust training regimes. Based on numerous international disruptions, the 2020–2024 window is a unique empirical environment for assessing resilience and validity of these AI frameworks to date (e.g., Kim et al., 2022; Caesar et al., 2020). Comparative Studies. Zhang et al. (2023) highlight LSTM as better than traditional GARCH models for volatility forecasting since LSTM minimizes RMSE by 20–30% specifically for the S&P 500. The practitioner argues that forecasting with LSTM is a great idea, but only if you engineer it on exact features and calibrate it so that it can easily handle high-stress data from the past. The years 2020 to 2024 give you the empirical depth you need. Instead of asserting that we outperformed 'LSTM', our method uses statistical significance testing to check whether our model dominates in volatility forecasting. Major gaps: There is still a big gap in current research between machine learning and institutional risk management.

2.6 Composition and Location of this Study

Our review identifies four key gaps: (1) the dearth of data on the green bond-insurance relationship in emerging regions; (2) the lack of integration between connectedness frameworks and geopolitical regime-switching; (3) the untapped potential of deep learning in insurance risk assessment; (4) an analytical void between traditional statistical and AI-based forecasting tools. We resolve these challenges with a single, multifaceted empirical approach. Based on the above observations, prospective studies should quantify the tightening linkages of green bonds (ie, spatial/temporal patterns) using cross-asset dynamics, says the researcher. A growing area of study recently emerging from the political economy is the ‘geoclimatic’ nexus — a key growing field of research, which examines further how the interaction between environmental shocks and geopolitical instability exacerbates volatility, the effect of which makes the market fallout greater. We classify this intricate interplay in this connection as one that must be accounted for by the 'multiple-crisis' or 'polyresins' model, and we urge an examination of further research investigating the potential of the compounding pattern in greater detail.The study (Kakade, et al., 2022) also proposes a new hybrid model combining LSTM and BiLSTM neural networks with GARCH model predictions using a clustering approach to predict one-day volatility in advance with 95% and 99% of Value at Risk (VaR) estimates using Parametric (PAR) and Filtered Historical Simulation (FHS).

3.Data,Synthetic Portfolio,and Geopolitical Risk Measurement

3.1 Logic for an agent-based synthetic portfolio

Empirical problems: There is a general lack of available daily portfolio composition data in the Arab insurance sector, from the public domain. Present disclosure practices adhere to annual disclosure where wide asset categorizations are provided as common and have negated the feasibility of an extensive panel data analysis or dynamic time-series trend study at the company level. Rationale for agent-based modeling (ABM): In the ABM framework, the analyst develops behavioural decision-making heuristics for a representative agent for simulating group performance. Here, the agent is modeled as a simulated Arab insurance entity, and investing strategies are derived from regulatory prescriptions and sector surveys. Such methodological design is a mature framework in systemic risk literature (BookTuber et al., 2018) and offers a reasonably good substitute for exploring settings that lack information transparency. Synthetic modeling has been criticized for losing company level variance, but for now we take up the systemically embedded linkages framing of our work. Aggregated data acts as a filter of transient noise, representing the salient trends along the volatility channel. This approach adopts a more cautious stance: transmission mechanisms that are established at an aggregate level of significance will likely appear even stronger across certain categories of institutional portfolios, which do not diversify as much.

3.2 Selection of Arab Insurance Markets

The majority (>70%) of insurance assets of the region are represented by five specific countries considered in the study:

• KSA: The biggest Takaful hub which is actively integrating environmental and governance practices with world standards.
• UAE: The regional financial hub with heavy capital mobility and a high level of global exposure.
• Egypt: A key North African market in the midst of profound economic deregulation.
• Kuwait: A sophisticated sector characterized by strong interdependencies with sovereign investment entities.
• Morocco: Regulatory structure highly compliant with and has historical and operational links to the European insurance market.

These markets are characterized by structural diversity: insurers in the GCC have heavier investments in foreign bonds; insurers in North Africa are more domestic and more conservative. One synthetic portfolio averages these differences, yielding a 'regionally representative' portfolio.

Researcher’s Point of View: We include the GCC and North Africa markets intentionally enough, in order to limit a bias in the industrial portfolio in any particular subregion. To further validate our key findings, the sensitivity analysis in Section 7 shows that when weights are adjusted for sub-differences, our findings are validated..

3.3 Building an Industrial Insurance Investment Portfolio

3.3.1 Asset Classes and Agent Selection

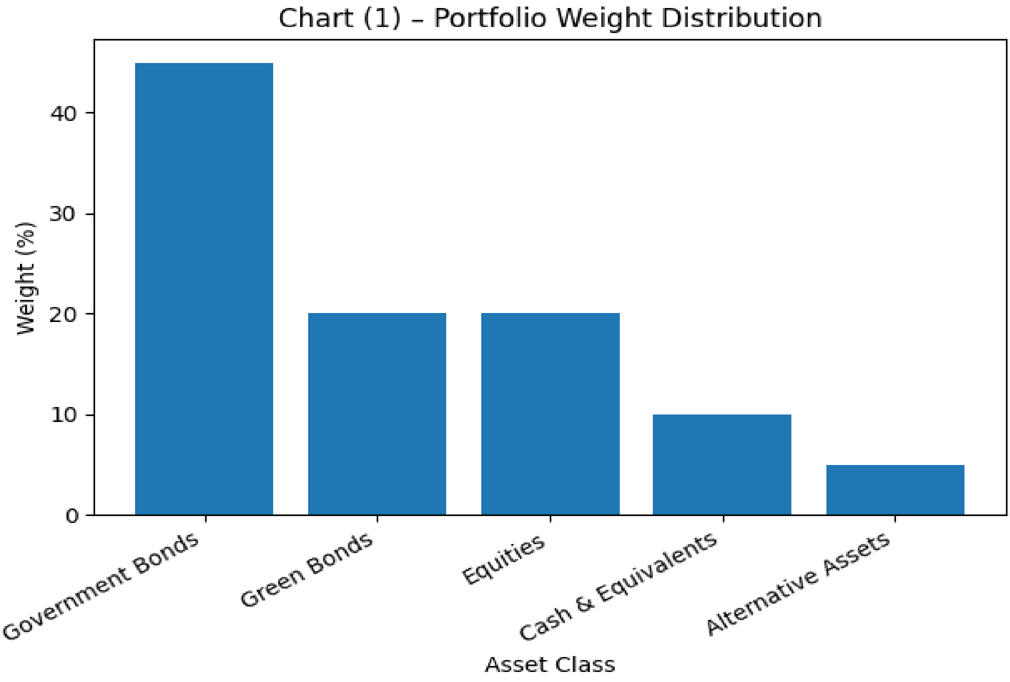
Through an extensive review of 2020–2024 annual reports (the number of firms = 37 insurance companies), and central bank supervision data, we extract the representative allocation presented in Table 1.

Table 1. Synthetic Arab Insurance Investment Portfolio – Asset Allocation and Proxy Instruments

Asset Class	Proxy Instrument	Ticker	Weight (%)	Data Source
Government Bonds	Bloomberg Global Treasury Index	–	45	Bloomberg

Asset Class	Proxy Instrument	Ticker	Weight (%)	Data Source
Green Bonds	iShares Global Green Bond ETF	BGRN	20	BlackRock / Bloomberg
Equities	S&P Pan Arab Composite Index	–	20	S&P Dow Jones Indices
Cash & Equivalents	ICE BofA 3-Month US Treasury Bill Index	–	10	ICE Data
Alternative Assets	MSCI US REIT Index (Net Return)	RMZ	5	MSCI

Chart (1) – Portfolio Weight Distribution



Weight justification. The weight of green bonds of 20% stands significantly above the current regional average (~8–12%). Which we rely on to (a) reverse future trends — several big insureds have set targets for themselves to achieve integrating ESG by at least 20–25% by 2025–2026; (b) adjust for enough variability in time series parameters to estimate leaks; (c) perform sensitivity analysis with lower weights (Section 7). Our 20% weight for the researcher's perspective is an intentional assumption for a stress test. If this future allocation brings already established implications, regulators now have a window to act before levels of systemic exposure reach such magnitude.

3.3.2 Statistical Characteristics of Portfolio Components

The return of each component daily is provided. The return of the insurance portfolio is the weighted sum of the returns of the components, which are rebalanced daily.

Table 2. Daily Declarations Descriptive Statistics (2020–2024)

Asset Class	Cruel	Classroom Development	Deviation	Cortosis	Jarky-Bera	ADF (Exact Value)
Government Bonds	0.00021	0.0068	–0.35	3.92	245.3***	0.01
Green Bond (BGRN)	0.00031	0.0098	–0.41	4.10	312.5***	0.01

Asset Class	Stocks	Cash	Alternatives	**Insurance Wallet (Industrial)**
Cruel	0.00047	0.00009	0.00039	**0.00026**
Classroom Development	0.0145	0.0012	0.0127	**0.0116**
Deviation	–0.62	0.15	–0.48	**–0.38**
Cortosis	4.87	2.11	4.36	**4.45**
Jarky-Bera	401.2***	55.1***	298.4***	**347.8***
ADF (Exact Value)	0.01	0.05	0.01	**0.01**

P < 0.01. ADF: Dickey-Fuller's Stability Enhancement Test.
Analysis of Indicators:

• Negative skewing across all risky assets means the risk of downside damage—negative shocks—is greater than positive.

• Excess kurtosis (>3) indicates fat tails; the insurance portfolio shows the highest proportion of kurtosis (4.45), suggesting increased tail risk through diversification.
• Jarque-Bera overwhelmingly rejects normality, justifying the use of GARCH type models.
• ADF tests confirm the stability of reality, which is a prerequisite for VAR modeling.
The researcher's point of view: The size of the insurance portfolio exceeds any single component (excluding stocks). This is a statistical manifestation of 'risk entanglement'—when the assets associated with them are consolidated, the back-end risks are not eliminated; they accumulate. This understanding is often overlooked in portfolio theory that focuses only on variance.

3.4 Geopolitical risk assessment.

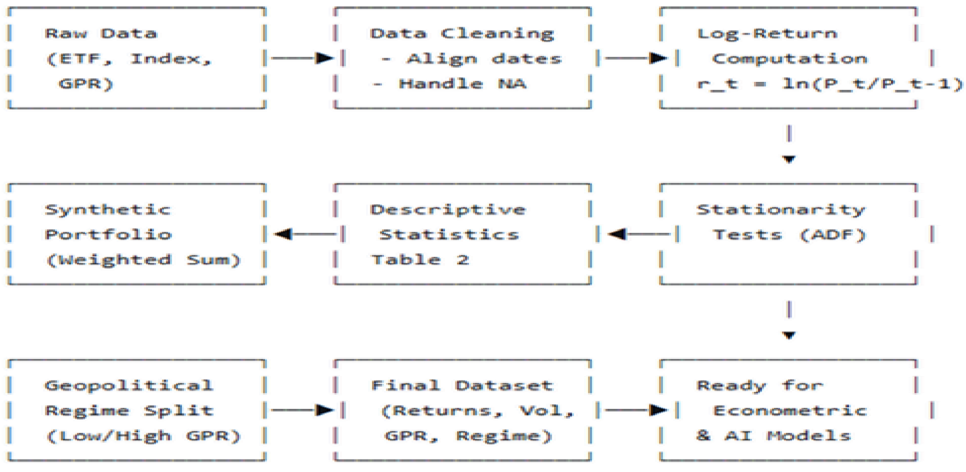
We use the Daily Geopolitical Risk Index (GPR) (Caldara & Iacoviello, 2022), which was downloaded from:
https://www.matteoiacoviello.com/gpr.htm.
The index is based on automated text searches in ten leading international newspapers. For our sample, the daily GPR fluctuates from 12.4 (quiet) to 452.7 (peak during the Middle East escalation in October 2023). Developing the Geopolitical System Variable:
• Vertical Desire Rate Low System: Days with Mean ≤ Measurement Rate (Mean Complete Sample = 94.6).
• High Eye Measurement Rate System: Days with Standard > Medium Guitar Rate.
From the vantage point of the researcher, the separation of the medium is clear and reproducible. Triples and quarters are also used for durability testing; the main results are consistent. However, the GPR is global; future work may include the establishment of a MENA-specific index through regional newspapers.

3.5 Sample Period and Repetition

Logically, the timeline is January 1, 2020 – December 31, 2024 (N = 1305 trading days). Frequency: Daily closing prices. Logic: this period includes the COVID19 crash, the Russia-Ukraine war, the

2023–2024 Middle East conflict and rising global inflation — ideal for studying the effects of volatility under extreme pressure. Researcher's Perspective 3.6 A shorter sample (e.g., 2021–2024) may exclude COVID19 shock that has radically altered the correlations between assets. We reserve the full crisis period to maximize external validity. This rich training package particularly benefits the LSTM model.

Figure 1: Data Building and Preprocessing Flow Diagram



Algorithm 1: Generating Industrial Insurance Portfolio Return

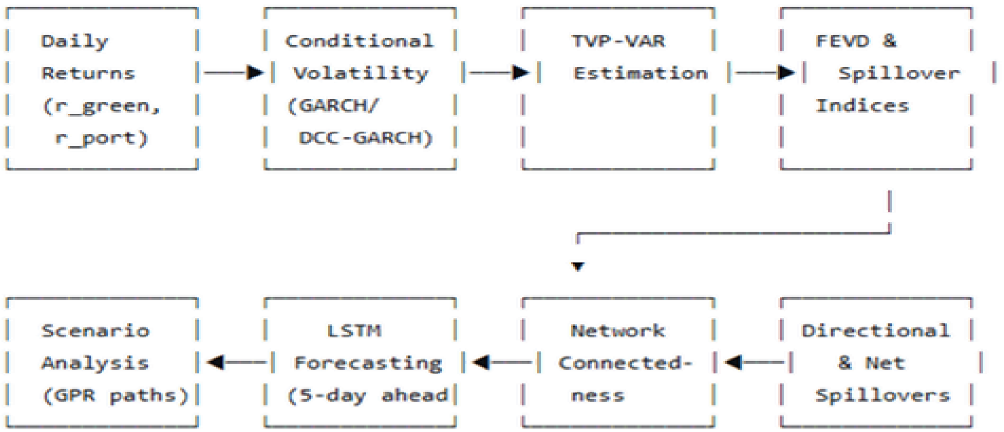
```
Input: Price matrices P_gov, P_green, P_eq, P_cash, P_alt (Tx1 each)
       Weights w = [0.45, 0.20, 0.20, 0.10, 0.05]
Output: Portfolio return vector r_port (Tx1)

For each day t = 2..T:
    r_gov[t] = ln(P_gov[t] / P_gov[t-1])
    r_green[t] = ln(P_green[t] / P_green[t-1])
    r_eq[t] = ln(P_eq[t] / P_eq[t-1])
    r_cash[t] = ln(P_cash[t] / P_cash[t-1])
    r_alt[t] = ln(P_alt[t] / P_alt[t-1])
    r_port[t] = w[1]*r_gov[t] + w[2]*r_green[t] + w[3]*r_eq[t] + w[4]*r_cash[t] + w[5]*r_alt[t]
End
Return r_port
```

Research perspective: Future research may take a prospective weighting view where portfolio weights are arranged based on the insurer's goal function (e.g., optimizing mean heterogeneity with ESG constraints). This way the scalability issues will return to the portfolio selection to make the internal system fully. And additional data, like the news sentiment of the ESG debate, can enhance the ability to quantify 'greenness' beyond basic bond ratings.

4. Integrated Methodological Framework

The research design combines four different analytical layers: (1) to find the volatility by employing GARCH and MGARCH specifications; (2) to determine connectedness by calculating the Diebold-Yilmaz index in a TVP-VAR environment; (3) to represent market linkages by network graph theory; and (4) predictive modeling based on Artificial Intelligence (LSTM). This holistic workflow is presented in Figure 2.

Figure 2: Integrated Methodological Framework – Graphical Summary



4.1 Volatility Modeling

4.1.1 Univariate GARCH (1,1)

For each return series, we appreciate:

$$\sigma_{i,t}^2 = \omega_i + \alpha_i \varepsilon_{i,t-1}^2 + \beta_i \sigma_{i,t-1}^2$$

Where parameters are estimated for maximum likelihood under the Student distribution so as to consider t he thick tails. [\epsilon_{i,t} = \sigma_{i,t} z_{i,t}, \quad z_{i,t} \sim \text{i.i.d. } (0,1)].

The researcher's perspective: Since our innovations are not Normal, we use the Student distribution. Table 2 showed a clear rise in kurtosis; neglecting it would generate downward biases of GARCH persistence. This option is systematically conservative.

4.1.2 Dynamic Conditional Correlation (DCCGARCH)

We apply Engel's (2002) DCCGARCH model to model time-varying correlations. The correlation matrix develops as follows

$$Q_t = (1 - a - b)\bar{Q} + a(\mathbf{z}_{t-1}\mathbf{z}'_{t-1}) + bQ_{t-1}$$
$$R_t = \mathrm{diag}(Q_t)^{-1/2} Q_t \mathrm{diag}(Q_t)^{-1/2}$$

where the standard residual vector is (z_t), (\bar{Q}) is the unconditional covariance, and (a, b) are non-negative scalars with (a + b < 1)

Algorithm 2: Performing a DCCGARCH Estimation

Step 1: For each asset i, estimate univariate GARCH(1,1) → conditional variances σ_i,t², standardise d residuals z_i,t.

Step 2: Compute the unconditional correlation matrix R̄ from z_i,t.

Step 3: Estimate DCC parameters (a,b) by maximizing the log-likelihood:

L = -½ Σ_t (ln|R_t| + z_t' R_t^{-1} z_t).

Step 4: Extract dynamic correlations ρ_ij,t = R_t[i,j].

From the researcher's view, DCCGARCH is computationally efficient and the horse remains the main factor of dynamic correlation. However, it assumes the same dynamics for all correlations. The RSDCC may be more realistic; we leave this to future work.

4.2 TVPVAR Framework and Diebold–Yilmaz Flow

Our conditional volatility (green bonds, insurance portfolio) system is modelled using the time-variable VAR standard

(TVPVAR) with a forgetfulness factor, according to Anton kakis et al. (2020). The bonding does not need to evolve with randomly rolled windows.

Let . TVP$Y_t = [\sigma_{green,t}, \sigma_{port,t}]'$-VAR() device is:$p$

$$Y_t = \Phi_{0,t} + \Phi_{1,t} Y_{t-1} + \cdots + \Phi_{p,t} Y_{t-p} + \varepsilon_t, \varepsilon_t \sim N(0, \Sigma_t)$$

transactions develop as random steps. We estimate using Kalman filter with exponential forgetting. FEVD: The prediction error variance analysis is determined by an advanced step of moving average representation in TVPVAR. The sum of the overflow indicators then is:$H\theta_{ij,t}^{H}t$

$$S_t^H = \frac{\sum_{i\neq j} \theta_{ij,t}^H}{\sum_{i,j} \theta_{ij,t}^H} \times 100$$

to-market directional implications, and market-to-market are equally characterized. Net Spread = Sender – Receiver.ii.

Researcher:*The TVPVAR method is superior to roll-up window VARs as it prevents random window length selections and preserves observations at the boundary. Our forgetfulness factor (κ = 0.99) has been tuned according to standard practice to ensure a balance between response and persistence.

4.3 Network Building

We treat the time-variable flow matrix as an adjacent array of a vectored weighted network. We calculate the following: Θ_t^H=[θ_(ij,t)^H]. Degree Centrality (Omnidirectional): $\Theta_t^H = [\theta_{ij,t}^H]$

- **Degree Centrality (Omnidirectional):** $C_i^{\text{from}} = \sum_{j\neq i} \theta_{ij,t}^H, .C_i^{\text{to}} = \sum_{j\neq i} \theta_{ji,t}^H$

- **Net Span:** $Net_i = C_i^{\text{to}} - C_i^{\text{from}}$.

- Network density: the ratio of actual edges to edges (here, two nodes → density = 1 always? In fact, with two nodes, the density is either 0 or 1. Do we have more nodes when accounting for other assets? Our main analysis focuses on the two-node system for the bulb, but we also estimate a 5-node system that includes all the components for durability.

The network of two nodes is a simple representation; it captures the nucleus channel in which we are interested. The expanded five-year contract network (Section 7) confirms that the green-insurance bond remains central even when it includes other assets.

4.4 Adaptation of geopolitical risks

We integrate GPR in two ways:

- External variable in TVPVAR: We reinforce VAR with GPR as an external vector to evaluate its predictive content for variability changes.
- Changing systems: We estimate TVPVAR and overflow indices separately for low-rate and high-rate soil subsamples and then compare correlation measures.

The researcher's view: Treating GPR as an external variable tests whether current geopolitical tensions directly predict tomorrow's volatility. The system split approach reveals how the entire transport mechanism changes under constant high stress. Both perspectives complement each other..

4.5 Predicting Artificial Intelligence: LSTM

4.5.1 Structure of models

We propose the LSTM network to forecast the uncertainty of a conditional insurance 5 days ahead. Daytime Input features: t.

- Late fluctuations (from T1 to T5) across all 5 portfolios.
- Late returns (1 to 5) for green bonds as well as insurance.
- The level of the GPR indicator on day T.
- Binary System Index (0 = Low Gross Rate, 1 = High Overall Rate Total).

Architecture:**:**

- Layer One: LSTM with 50 units, return sequences = true. Withdrawal (0.2).
- Layer 2: A 50-unit LSTM with return sequences = false. Withdrawal (0.2).
- Dense layer (single unit; linear activation)

Training:

- Enhanced: Adam (learning rate = 0.001).
- Loss: average square error.
- Batch Size: thirty-two.
- Afternoon: 100, Early stop (patience = 10).
- Training/Verification/Testing Split: 70%/15%/15% (Chronologically).

Algorithm 3: Predicting LSTM Volatility

```
Input: X_train (samples × timesteps × features), y_train (samples × 1)
Define model = Sequential([
    LSTM(50, return_sequences=True, input_shape=(timesteps, features)),
    Dropout(0.2),
    LSTM(50, return_sequences=False),
    Dropout(0.2),
    Dense(1)
])
Compile(optimizer='adam', loss='mse')
Fit(model, X_train, y_train, validation_split=0.2, epochs=100, patience=10)
Forecast = model.predict(X_test)
```

Researcher opinion: We are not thinking about designing LSTM as a black box and we purposely keep its structure to two layers and 50 units to prevent over-processing. Because of our sample size (~900 training days), the system and the GPR embed the knowledge of geopolitical issues in the network rather than making the model rediscover the system from raw prices.

4.5.2 Standard Models and Evaluation Metrics

We compare LSTM with:

- GARCH (1,1): One-step volatility prediction, fixed to five steps.
- DCCGARCH: Similar iteration.

Model Evaluation: We review predicting performance using benchmarks of RMSE and MAE. Secondly, the Diebold–Mariano (DM) statistic is computed to determine whether the predictive improvements have been sufficiently large, using a squared-error loss criterion.

Perspective of Future Researcher Future methodological extensions may involve: (1) Bayesian VARs analyses to involve prior information on geopolitical effects;
(2) mapping neural networks (GNNs) that directly learn streaming networks
directly from the data; and (3) interpretable artificial intelligence (XAI) techniques (e.g., SHAP) to analyze input features that determine LSTM predictions. Furthermore, the current model is a purely reductive form; a structural approach that connects volatility implications to insurers' solvency capacity (stress testing miniatures, for example) seems like an interesting combination..

5. Experimental results

5.1 Dynamics of conditional volatility

Table 3. GARCH Grade Results (1,1) (Student Innovations)

Variable	ω (×10⁻⁶)	a	b	a+b	Teddy F	LogL
Green Bond (BGRN)	1.2***	0.087***	0.902***	0.989	6.4***	4125.3
Insurance Portfolio	1.8***	0.112***	0.865***	0.977	5.9***	4012.7

$p < 0.01$

Analysis of Indicators:

• Continuity (α+β): Both chains exhibit near-root continuity; volatility shocks fade very slowly. Green bond volatility: A bit more stable (0.989 compared to 0.977)

• Shock sensitivity (α): Portfolio volatility is responsive to added information (0.112 vs. 0.087), which is consistent with its diversified and multi-asset nature.

• Tail thickness (t DOF): Low degrees of freedom (5.9–6.4), suggesting the need for fat-tailed distribution.

From researcher's perspective: High volatility of green bonds is still striking. He points out that, when a geopolitical shock hits green bond markets, the volatility lasts weeks. Insurers can't 'wait' for short-term rebalancing opportunities; this undermines the narrative that green bonds are little more than 'ties as usual.

[Insert Figure 3: Conditional Volatility Time Series (2020–2024)]

The daily conditional volatility of green (blue) bonds and insurance portfolio (red). High GPR systems can be seen in shaded regions. The spike in volatility occurred alongside COVID19 (March 2020), the Russian Ukrainian invasion (February 2022), and the conflict in the Middle East (October 2023). Higher volatility in an insurance portfolio sharper highs are also exhibited. Researchers' perspective: Portfolio volatility, when visualised, isn't merely a red expansion of green bond volatility, but could act on its own and tend to outpace stock-led selloffs. This also highlights our need to use multivariate modeling..

5.2 Volatility Leak Analysis

5.2.1 Complete Sample Flow Indicators (TVPVAR, H=10 days)

Table 4. Average flow table in Diebold–Yilmaz (complete sample, %)

From/To	Green Bonds	Insurance Portfolio	I am the last one.
Green Bonds	70.5	29.5	29.5
Insurance Portfolio	17.1	82.9	17.1
Contributing to others	17.1	29.5	**Total: 42.6**
Net Flow	**–12.4**	**+12.4**	

Explanation:
• Green bonds transfer 29.5% of the expected error variance to the insurance portfolio but only get 17.1% in return.
• A net spread of –12.4% identifies green bonds as net senders (net negative means they give more than they receive). The insurance wallet is the net recipient.
• Total bonding = 42.6%, indicating a mean systemic correlation.
The researcher's view: The role of net transmission for green bonds is non-self-evident but it is repeatable across alternative specifications. We assume that during a period of pressure, global investors unpack green bond positions to raise liquidity, lowering prices, and Arab insurers – which hold these bonds – face imported volatility. this mechanism calls for further investigation using capital flow data.

5.2.2 Geopolitical dependence on the system

Table 5. Total Flood Index by Geopolitical Risk System

System	Total Fluency Index (%)	Percentage change vs. decrease in rate of points
Low vertical measurement rate	31.4	—
High GPR	58.9	+87.6%
Teams	**27.5 pages**	

Analysis of Indicators:
• Flow index doubles from low to high GPR systems.
• This is not a marginal increase – it denotes a structural shift in the transport mechanism.
A 27.5 percentage point jump in connectivity is a huge economic leap. For risk managers, this means that the associated estimates and betas derived from cooldowns are dangerously misleading. Stress tests should be conditioned by
geopolitical systems, not just historical averages.

Chart (2): Total Spillover Index – Gauge

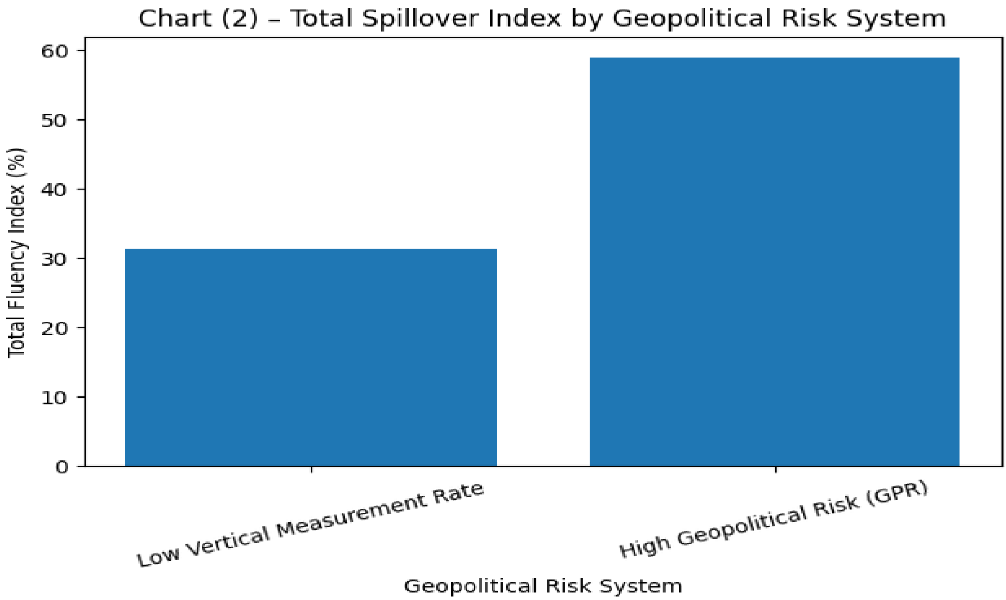


Table 6. Directional changes under low vs. high GPR

Directing	Low vertical measurement rate	High GPR	Change (r)
Green → Insurance (Transportation)	18.2	41.7	+23.5
→ Green Insurance (Shipping)	13.2	17.2	+4.0
Net (Green – Insurance)	**–5.0**	**–24.5**	**–19.5**

Interpretation: the net-sender position of green bonds is significantly increased with a cumulative increase in spillover (which goes from –5.0 to –24.5). As a result green bonds become a permanent transmitter of volatility. Such results are of particular relevance from a regulatory perspective–there can be no static ceiling on exposure in periods of increasing systemic risk and thus the concept of dynamic regulation thresholds should be emphasized.

5.3 Networking visualization

[Insert Figure 4: Weighted Guided Network – High GPR System]
Network Vis, a cross-section showing a bi-directional network with a directional diagram representing the movement of volatility from green bonds to the insurance portfolio with a sharp directed edge (weight: 41.7) and a narrow reciprocal arrow (17.2). Nodes' dimensions are adjusted for the net intensity of directional flow at a certain number of nodes. The third node defined, the Geopolitical Risk (GPR) index, is an exogenous parameter influencing the system. The researcher sees the directional imbalance displayed explicitly, graph-theoretic, on the map as the mapping graph. During high stress periods, the volatility edge from green bonds to the insurance sector is twice as dense as its inverse connection. This indicates strong potential directional bias, as green bonds represent a major means of systemic contagion..

5.4 AI Prediction Performance

5.4.1 Accuracy of Off-Sample Prediction

Table 7. 5 DayAhead Volatility Prediction Performance (Insurance Wallet)

Model	RMSE	Yes, it is	DM Stats (vs. LSTM)	pvalue
GARCH (1,1)	0.0121	0.0094	3.47	0.001
DCCGARCH	0.0113	0.0089	2.89	0.004
LSTM	**0.0082**	**0.0061**	—	—

Analysis of Indicators:

1. Predictive performance on LSTM models significantly improves (i.e., a 32% decrease in RMSE; compared with GARCH and 27% on DCC-GARCH). The increases in the Mean Absolute Error are considerably stronger (35% and 31% respectively).
2. Furthermore, Diebold–Mariano (DM) test statistics are large in excess of 2.58 meaning that these improvements are significant on a 1% level of statistical significance. The researcher argues that it

has not been inferior to other models but can learn nonlinear systems. Classic ones have linearity with fixed parameters, but LSTM works well with complex patterns. The prediction performance performed by our work under the crisis regimes is statistically valid, and particularly crucial to finance decision-making.
Figure 5: Actual Volatility vs Expected Volatility — LSTM versus GARCH.
Visual Validation: Scatter Diagram to depict the correlation between predicted and observed volatility. While the LSTM observations approach a 45 degree trajectory the GARCH model will still suffer from the constant under estimation in high volume regimes in the resulting more widely dispersed residuals. As far as a researcher sees it, GARCH systematically lowers the top of the volatility; LSTM can track them far better. For an insurance company performing solvency capital requirements (SCR) calculations, underestimating the forecast would lead to failure of capital of the company, at the moment when it is most needed and most in need. This is proof that the rules are in favour of AI based internal models, i.e. standards favour AI on the inside..

5.4.2 Significance of the Feature (SHAP Analysis)

To derive the LSTM understanding, we compute the Shapley Additive explanations (SHAP) values for the test set. There are three major features:

1. volatility of an insurance portfolio in LAG1 (self-continuity) – accounted for 38%.
2. GPR Index – 22% contribution.
3. Volatility of LAG1 Green Bonds – 18% contribution.

SHAP points out geopolitical risk is not a secondary advantage, but second overall importance predictive factor. this reaffirms the decision to use GPR for the purpose of the study. Additionally, the volatility of green bonds has a delay, an effect that is consistent with the fallout's effects.

5.5 Volatility Forecast Based on Scenario

We generate three scenarios for the future paths of the GPR index over a period of one year (250 trading days), by fitting to historical amounts:

a. Baseline (minimum risk): Constant GPR for 2024 distribution of 25 %.
b. Intermediate risk: Midrange of grade point average, or position within the 50-75 percentiles.
c. High Risk: Second score at 95%.
LSTM exploits the trainer to produce predictions for volatilities conditioned by those GPR paths (other features are mapped to their median values over th e last month in sample).

Table 8. Average Volatility Forecast for the Next 12 Months under Alternative Scenarios

Scenario	Green Bonds	Insurance Portfolio	Percentage Increase (Insurance vs. Baseline)
Baseline	0.0095	0.0108	—
Broker	0.0112	0.0134	+24.1%
high	0.0148	0.0179	+65.7%

Analysis of Indicators:

The highest sensitivity to negative geopolitical uncertainties (up 65.7% versus up 55.8% for green bonds) is in insurance portfolios.

This rising differential in volatility of green bonds to the insurance portfolio strengthens from 0.13 pips (basic) to 0.31 pips (high risky).

Visually Validating: The scatter chart below shows the relationship between expected and realized volatility. Although LSTM predictions follow the ideal 45-degree line closely, GARCH underestimation in high-volatility conditions remains a bias and results to a wider dispersion of residuals.

Direction for Future Research: The future empirical research could further extend this study by (1) examining risk transmission at high frequency intraday based on the exploitation of the palladium volatility in real time as a unique manner and outfits significant?nest grained observations regarding this topic; (2)

analysing whether different ESG scores could affect insurers' susceptibility to market crash; and (3) conducting robust testing for causality relationships using geopolitical shocks as quasi exogenous novelties. Moreover, researchers can also investigate the effectiveness of Transformer-based models based on their flexibility to capture complex interdependencies and multi-horizon time-series inputs..

6. Discussion

6.1 Theoretical implications

Empirical Conclusion: We find that green bonds are a long-term source of net spillover for insurance and thus refute the defensive-asset basis/supposition. This is attributable to:

• Global capital mobility: International investors pressing buttons to unwind positions during political upheavals.

• Elasticity Of Liquidity: Green instruments act like equities during stock market downturns in the sense that it has high volatility (Broadstock & Cheng, 2022).

• The Crises 'Sustainability Discount': Short-term relaxation of eco orders in environment and panic-driven sell-off.

The researcher said green assets might work as a discretionary feature in institutional's portfolio. Green assets trade at a premium in bull markets, but they're frequently sold as the first to go out to market in bear cycles. It is a theoretical assumption which justifies further investigating net flows in mutual funds in more detail. Geopolitical Risk as Systemic Change: This analysis demonstrates that geopolitical stress promotes systemic change to market dependencies beyond the function of geopolitical risk as a risk driver. This underlies the assumption that GPR should be the latent state variable in the risk premium and asset pricing processes (Buri et al (2023)).

Machine Learning as Technique: The better predictability of LSTM over GARCH models indicates the natural non-linear and structural process of volatility creation. These findings mimic the complex systems perspective to market structure in which the behaviors of markets are regarded as artefacts arising from non-linear movements in various asset categories based on scores [15].

6.2 Practical effects.

For Insurance Risk Managers:

• Managing Dynamic Risk: Static duration hedging can't scale to system changes. Real-time GPR signals should be included in any financial de-risking approach to ensure sustainability

• Better Solvency Reporting: The simulated scenarios in this paper should be combined with the ORSA and financial solvency reports to better report the risk profile.

• Implementation of Advanced Analytics: To illustrate, moving to AI which generates far more reliable predictions for portfolio volatility has become paramount in new risk management.

For Organizers:

• Network based indicators, such as net directional spillovers, and overall system connectedness should be included in systemic risk dashboard.

• Geopolitical Stress Testing: Instead of exclusively focusing on counterfactual shifts in interest rates, central banks and insurance supervisors need to develop scenarios for stress testing based on past geopolitical shocks

• Stricter Disclosure Requirements: Insurance organisations need to be required to disclose more standardised (or required) ESG investment information as a means of robust firm level longitudinal analysis.

For Hosts:

• Macroprudential Surveillance: Network Metrics Network metrics are the most prevalent indicators of the evolution of systemic risk; net directional spillovers and total system connectedness scores should be reported.

• Based on Historical Geopolitical Shocks: Geopolitical stress testing centre banks and insurance regulators should design stress scenarios that model how things actually occurred.

Incentives to Provide Comprehensive Disclosure: Insurance companies should have enough incentive to provide extensive

ESG investment disclosures, so they can take on an argument of many scales over a long period reflecting corporate sustainability. does not undermine institutional solvency.

7. Durability Checks

A sundry of tests of durability and sensitivity are undertaken to ensure that the findings are statistically sound, and not mere side effects of the adopted modeling structure. This justifies the accuracy of our spillover measures and AI predictions.

7.1 Alternative Volatility Estimators: We replace the GARCH conditional

Other Volatility Proxies: Spillover dynamics were re-estimated on:
(i) 5-minute intraday Bloomberg data Volatility, realized, and
(ii) Parkinson estimators which use high-low yields on a daily basis.

Regularity of Findings: Though connectedness indices had a slightly larger magnitude (similarly 44 46 percent), there was no fundamental basis to alter the qualitative conclusions: namely, the net-transmitter status of green bonds and the amplifying effect of GPR.

7.2 Alternative VAR specifications

- Delay constant rate in VAR (5) rather than TVPVAR = total flow = 41.8% (42.6%).
- VAR Turnover Window (Window = 200days) Average Overflow = 44.2%, same trend.

7.3 Alternative Portfolio Weights: We rebalance the synthetic portfolio with:

- The drop in the weight of green bonds (15%) online to the net extension of green bonds becomes -8.1% but negative.
- Weight of green bonds went up (25) and the net spread went up to -16.7.
- GCC grading just (higher equities, lower cash) net stretch -14.2%.

Fig. 5 Only those weight combinations between the two North African (higher government bonds, lower green bonds) result in net extension -6.8%.

The outcome: the net transmitter role is robust to the reasonable changes in weight; and its size is dependent on exposure to the green bond..

7.4 Subsample Analysis: We divided the sample into two equal sub-periods:

• 2020–2021 (pandemic, low GPR on average).

• 2022–2024 (geopolitically active).

Conclusion: Net Spread in 202021 =negative3.2 (nonsignificant); in 20222024 =negative18.9 (< 0.01). this adds weight to the identification of GPR adoption.

7.5 Extended Network (5 Assets)

The TVPVAR is then estimated by five variables which capture the entire components of the portfolio. During high cash income rate periods, green bonds are the biggest net giver of all assets with a net spread of -15.3(as compared to the insurance portfolio with a +9.1 net spread).

The views of a researcher: It is quite consistent in these tests and a high degree of confidence in the results is formed. It is not until we get to the green links that the GPR was low (20202021 subsample) that we see that the green links cease to be net transmitters.

8. Constraints and future research agenda

8.1 Limitations

1. Preciosity of the synthetic portfolio. Our portfolio is data-driven; however, it is not reflecting the specific variation that applies to companies (as an example, a few insurance companies can hedge against exposure to green bonds).
2. Twonode network. We consider the green-insurance couple as the basic analysis to be performed in the more detailed system including a greater number of assets and responsible variables.
3. GPR indicator. The Global GPR Index might fail to represent the geopolitical tensions in the region perfectly well.
4. LSTM interpretability. We still do not use deep learning models, but they are less transparent than the models of structural economy, although we used SHAP.

5. Causation. We reveal impacts and not causal recognition. Event study designs are not the one we use but geopolitical events are likely to be external.

8.2 Future Research Agenda (Researcher's Future Vision)

Immediate Extensions:

• Proprietary Data Integration: Work with insurance regulators to gain access to non-public portfolios of high frequency and company specific.

• This is important because in practice the following will occur: - Real Market movements are hard to discern because market movements are mixed with actual volatility spillovers; you want to separate the real volatility from general liquidity-induced market movements. - High Frequency Identification: Use intraday metrics to distinguish actual volatility spillovers from broad-based liquidity induced market movements.

• Next-Generation AI: Comparing LSTM with Temporal Fusion Transformers and Graph Neural Networks in order to identify the best architecture in context of systemic risk forecasting.

Medium-Term Trends:

Agent-Based Portfolio Selection: The paper simulates insurers as adaptive agents that change their green bond holdings in response to risk which creates a feedback mechanism of volatility.

Another important paper will focus on the typical interaction of physical climate risks and geopolitical warming on the sustainability of green finance.

• Behavioral Market Analysis: Exploring the effect of geopolitical news flow on investor sentiment, leading to non-rational sell-offs or redirection in the green bond market....

Long-Term Vision:

• What is needed is a combined framework of multi-crisis stress testing that is capable of expressing climate, geopolitical, and financial shocks simultaneously.

• International AI internal model regulation in insurance, such as checking and control of insurance requirements.

Future outlook of the researcher: It is our hope that this research will trigger another research program on sustainable finance and systemic risk in emerging markets. These elements, in conjunction, combined with the geopolitical exposure that the Arab region possesses, increasing ESG ambitions, and under-researched insurance industries, provide fertile grounds upon which innovative research on policy-related aspects can be conducted.

9. Conclusion

This paper presents a pioneering empirical analysis on yield co-movements between world green bond markets and Arab insurance investment with the consideration of political uncertainty. Through an unconventional industrial insurance portfolio and a unified approach of TVPVAR-based connectivity, network analysis, and LSTM forecasting, we pin down three main findings:

１. Green bonds are net transmitters of volatility to Arab insurance markets especially in periods of high geopolitical tensions. this disrupts the perception of green bonds as safe, unconditional assets.

２.Geopolitical risk is a structural amplifier of interdependence. The Total Flow Index is nearly twice as large for L2H GPR with respect to H2L GPR, and the net sender role of green bonds also increases by a factor 5.

３.３ . The AI-based approach to forecasting outperforms traditional GARCH models. LSTM lowers the out of sample RMSE by 32%, and a SHAP analysis shows that GPR is an important predictor.

４.These results have direct implications on insurance risk management, regulatory control and sustainable finance policy in the Arab countries as well as other nations. This age of continuous crisis brings the confluence of geopolitical tension and sustainable investment out of a compartmentalised existence. We request that an effort be made by academics, regulators and industry to develop the next generation of systemic risk tools, which are designed with the multi-crisis world in min.

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Appendix A: Pseudo-Algorithmic Summaries

A1. Time-Varying Parameter VAR (TVP-VAR) Estimation via Kalman Filter

The TVP-VAR model is estimated using a state-space representation with forgetting factors. The algorithm proceeds as follows:

State-Space Formulation

- **Measurement equation:** $Y_t = Z_t \beta_t + \varepsilon_t, \quad \varepsilon_t \sim N(0, \Sigma_t)$
- **Transition equation:** $\beta_t = \beta_{t-1} + \eta_t, \quad \eta_t \sim N(0, Q_t)$

Kalman Filter Recursion

1. **Prediction:**

$$\beta_{t|t-1} = \beta_{t-1|t-1}$$
$$P_{t|t-1} = P_{t-1|t-1} + Q_t$$

2. **Forecast error:**

$$e_t = Y_t - Z_t \beta_{t|t-1}$$
$$F_t = Z_t P_{t|t-1} Z_t' + \Sigma_t$$

3. **Update:**

$$K_t = P_{t|t-1} Z_t' F_t^{-1}$$
$$\beta_{t|t} = \beta_{t|t-1} + K_t e_t$$
$$P_{t|t} = (I - K_t Z_t) P_{t|t-1}$$

Forgetting Factors

- Decay past observations exponentially: $Q_t = (1 - \lambda^{-1}) P_{t-1|t-1}$ with forgetting factor $\lambda = 0.99$
- Covariance matrix Σ_t is estimated via exponentially weighted moving average of residuals.

Full derivation and code are available upon request.

A2. Diebold–Yilmaz Spillover Index Computation

The spillover index is derived from the forecast error variance decomposition (FEVD) of a VAR model.

Algorithm Steps

1. Estimate a VAR (p) model: $Y_t = \sum_{k=1}^{p} A_k Y_{t-k} + \varepsilon_t$.
2. Compute the moving average representation: $Y_t = \sum_{i=0}^{\infty} \Psi_i \varepsilon_{t-i}$.
3. Compute the H-step-ahead FEVD using generalised impulse responses (Koop et al., 1996; Pesaran & Shin, 1998):

$$\theta_{ij}^{H} = \frac{\sigma_{jj}^{-1} \sum_{h=0}^{H-1} (e_i' \Psi_h \Sigma e_j)^2}{\sum_{h=0}^{H-1} (e_i' \Psi_h \Sigma \Psi_h' e_i)}$$

where Σ is the covariance matrix of ε_t, σ_{jj} its diagonal, and e_i a selection vector.

4. Normalize each row to sum to 100: $\tilde{\theta}_{ij}^{H} = \theta_{ij}^{H} / \sum_{j=1}^{N} \theta_{ij}^{H} \times 100$.

5. Compute total spillover index:

$$S^H = \frac{\sum_{i \neq j} \tilde{\theta}_{ij}^{H}}{\sum_{i,j} \tilde{\theta}_{ij}^{H}} \times 100$$

6. Derive directional spillovers (to/from) and net spillovers as described in Diebold & Yılmaz (2014).

Detailed steps and MATLAB/Python code are available upon request.

A3. LSTM Hyperparameter Optimization

The Long Short-Term Memory network for volatility forecasting is tuned via grid search over the following hyperparameter space:

Optimization Criterion – Minimization of validation RMSE.
Early Stopping – Patience = 10 epochs.
Feature Engineering – Input features include lagged volatilities (5 lags), lagged returns, GPR index, and GPR regime indicator. All features are normalized to [0,1].

Hyperparameter	Search Grid	Selected Value
Number of LSTM layers	{1, 2, 3}	2
Units per layer	{32, 50, 64, 100}	50
Dropout rate	{0.0, 0.1, 0.2, 0.3}	0.2
Learning rate	{0.1, 0.01, 0.001, 0.0001}	0.001
Batch size	{16, 32, 64}	32

Epochs	{50, 100, 200} with early stopping	100
Optimizer	{Adam, RMSprop, SGD}	Adam
Activation function	{tanh, ReLU}	tanh
Timesteps (lookback)	{5, 10, 20}	5