📊 When Global Fear Spikes, Who Flinches First?

By: Task Force Data Analytics DJPPR

***Data:** Jan 2008 – Dec 2024 | **Models:** VAR(15), Orthogonal IRF, GARCH(1,1) | **Variables:** ASEAN 10Y yield changes (bps), VIX level*

🔍 Introduction: Fear as a Global Transmission Channel

The VIX index—often referred to as the "fear gauge" of global markets—captures investor anxiety primarily from U.S. equities. But fear is rarely contained. When volatility spikes in New York, bond markets across emerging Asia often feel the tremors.

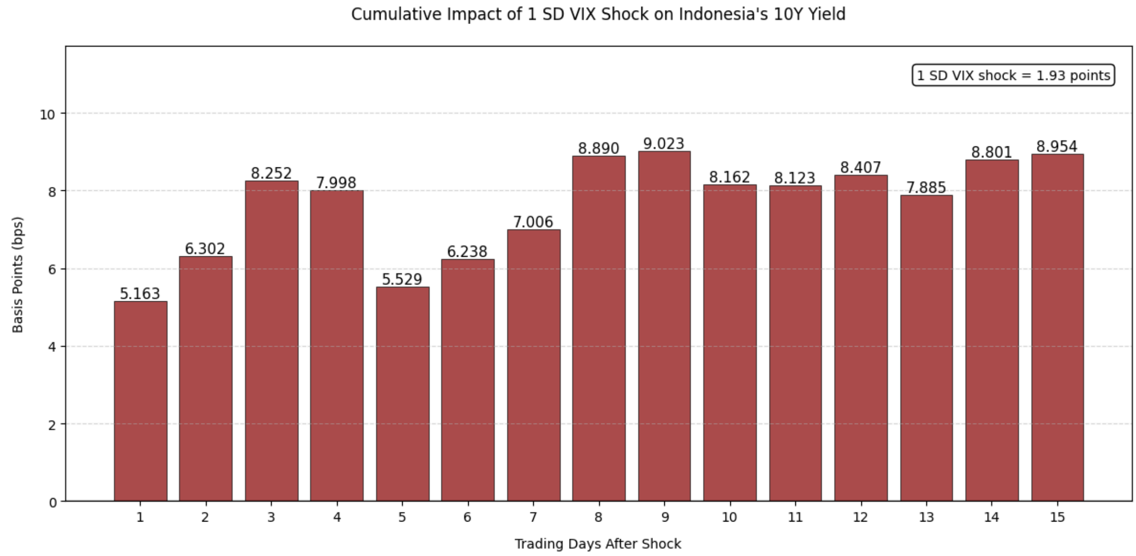
This report examines how 10-year government bond yields in ASEAN countries, particularly Indonesia, respond to sudden increases in global risk sentiment. The analysis employs a **15-lag structural VAR model**, with **orthogonalized impulse response functions (IRFs)** to isolate the pure effect of VIX shocks. Real-world yield changes are then derived by scaling IRFs with the standard deviation of structural innovations in the VIX. To complement this, **GARCH(1,1)** models are used to explore how long volatility lingers after a shock.

Among the four countries analyzed, Indonesia's response stands out—not just in magnitude, but in pattern and persistence.

🇮🇩 Indonesia: A Market That Reacts Swiftly and Doesn't Forget

Indonesia's 10-year government bond yields show a clear and sustained response to global volatility shocks. A structural VIX shock—approximating a 1.93-point rise in the VIX based on residual variation—leads to a **cumulative yield increase of 8.95 bps** over the following 15 trading days.

This response is not instantaneous. The adjustment occurs in phases. Initial moves emerge around day 2–3, followed by stronger reactions on day 4 and again around day 8–9. Rather than a one-off repricing, the Indonesian bond market seems to reevaluate risk in waves—first absorbing the signal, then confirming its persistence, before fully adjusting positioning.



Statistical diagnostics reinforce the signal. **Granger causality tests show significance across all 15 lags**, confirming the predictive role of VIX movements on Indonesian yields. Meanwhile, **IRF estimates are statistically significant across several horizons**, ruling out the possibility that the response is random noise.

The direction and consistency of the yield response point to a deeper behavioral pattern—one shaped not only by macro fundamentals, but by **persistent volatility dynamics**. That's where the GARCH model sheds additional light.

GARCH(1,1) estimates for Indonesia reveal a volatility profile that is both sharp and sticky. With $\alpha = 0.1838$ and $\beta = 0.8162$, volatility shocks hit fast—and linger. Their combined sum (~1.0) indicates near-unit persistence: once risk perception shifts, it remains elevated for days.

🧠 Interpreting Indonesia's Volatility Profile

The **α parameter** captures how sensitive the market is to fresh shocks. With $\alpha = 0.1838$, Indonesia's bond market reacts quickly to new information—yield volatility rises almost immediately after a VIX jump. This mirrors a "startle reflex," where traders reprice risk before macro data even has time to adjust.

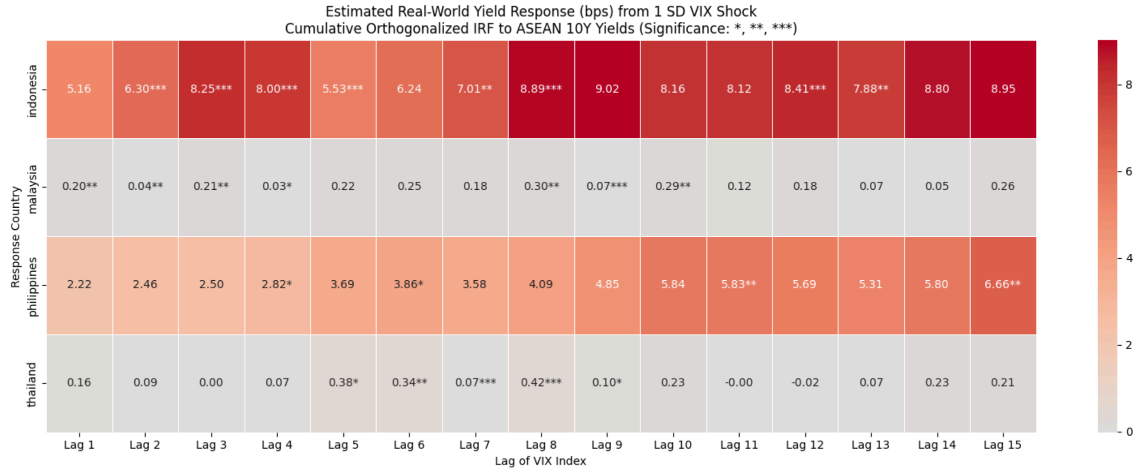
The **β parameter**, at 0.8162, describes how much of today's volatility is explained by yesterday's. The implication is behavioral: even after the VIX shock subsides, the market stays cautious. Spreads remain wide, liquidity thins, and participants adjust portfolios gradually.

Together, $\alpha + \beta \approx 1$ signals that Indonesia's bond market **doesn't easily forget fear**. The impact of a volatility shock carries forward—not just in yield levels, but in elevated uncertainty itself.

In effect, Indonesia's bond market does not merely react to fear—it absorbs it, reflects it, and retains it.

🌏 Other ASEAN Markets: Subdued, but Not Silent

While Indonesia's response is distinct in scale and depth, other ASEAN markets also exhibit meaningful patterns—though with more muted yield adjustments.



In the **Philippines**, yields rise by **6.66 bps** over 15 days. The adjustment is slower and smoother than Indonesia's, with responses peaking toward the second week. GARCH results show strong persistence in volatility, aligning with the delayed yield movements.

Malaysia's yield response is statistically detectable but economically modest—**just 0.26 bps** over the same period. The signal appears early and dissipates quickly. Yet volatility remains sticky, indicating that while traders register the shock, they don't translate it into sustained repricing.

Thailand registers the weakest yield reaction—**just 0.21 bps cumulatively**. The IRF curve fluctuates with intermittent significance. However, GARCH parameters suggest internal caution remains high, even without much change in observable yields.

🔁 Volatility Summary (GARCH Estimates)

Country	α (shock sensitivity)	β (memory)	α + β	Interpretation
Indonesia	0.1838	0.8162	≈ 1.0	Fast shock, sticky memory
Philippines	0.2197	0.7803	≈ 1.0	Moderate rise, long tail
Malaysia	0.0429	0.9571	≈ 1.0	Volatility without yield
Thailand	0.2930	0.7070	≈ 1.0	Volatility-led caution

Despite the variation in yield reactions, one trait is common across the region: **once volatility rises, it stays elevated**. This underscores that even when repricing is subdued, investor uncertainty remains.

📚 Methodology Summary

- **VAR(15)** selected based on AIC.
- **Orthogonal IRFs** computed from structural VAR, scaled using the standard deviation of VIX residuals (~1.93).
- **Granger causality** tested at lags 1 through 15 for each country.
- **GARCH(1,1)** applied to daily yield changes to model persistence in volatility.

📎 Appendix A — Indonesia's GARCH Profile in Focus

Indonesia's GARCH parameters describe a market with **fast-reacting and long-lasting volatility**. A high **α (0.1838)** means that yield volatility responds sharply to VIX shocks, even in the absence of fundamental changes. The **β (0.8162)** reinforces that once volatility is triggered, it decays slowly.

This profile creates a feedback loop: volatility invites caution, which in turn suppresses liquidity and sustains volatility. With **$\alpha + \beta \approx 1$**, the market exhibits near-unit-root persistence in uncertainty. This helps explain why the IRF curve does not revert to baseline quickly—**the reaction is not just rational; it's emotional and behavioral**.

📎 Appendix B — Why Granger Is Significant at Lag 1, but IRF Isn't

In Indonesia's case, **Granger causality at Lag 1 is statistically significant ($p = 0.0278$)**, but the **IRF at Lag 1 is not**. Though the IRF shows a yield response of 2.671 bps, it lacks statistical significance.

This isn't a contradiction—it's a reflection of two different tests:

- **Granger** tests whether lagged VIX data can predict today's yield.
- **IRFs** simulate how yields respond to a structural VIX shock over time.

The Granger result means that *lagged values of the VIX* hold forecasting value. But the IRF's lack of significance at Lag 1 suggests that the **initial reaction to a VIX shock isn't reliably different from zero**—the real movement builds later.

That's exactly what the IRF curve shows: stronger and more confident responses emerge at Lags 2–5. This delay also matches the timezone gap—VIX reacts to U.S. market close; Indonesia trades the next morning.

In short: Lag 1 has predictive value, but **the structural impact takes time to unfold**—a nuance that statistical significance helps uncover.

📎 Appendix C — Model Diagnostics & Structural Limitations

The VAR model used in this study passes the basic **stability check** — all characteristic roots lie outside the unit circle, confirming that the system won't explode over time. This ensures that the impulse responses we estimate are dynamically valid.

The **Durbin-Watson statistics**, all near 2.0, suggest minimal autocorrelation in residuals. On the surface, the VAR equations behave well — the past does not unduly contaminate the future.

But beneath that surface, two major red flags emerge.

First, the **residuals are not normally distributed** (Jarque-Bera p-value = 0.0). This breaks a key assumption behind standard IRF confidence bands — the tails are fatter than the model expects. Second, the **Portmanteau whiteness test** also fails (p-value = 0.0), meaning there's still structure left in the residuals even after using 15 lags. In other words, **the VAR hasn't fully captured the underlying dynamics**.

Taken together, these suggest that **some shocks are larger than expected, and some patterns remain unmodeled** — a potential issue when interpreting IRF significance or short-horizon causality.

🛠️ Appendix D — How to Improve the Model

This version of the model gives us a valid directional map — but it still misses nuance.

To improve future iterations:

- **Use bootstrapped IRFs** instead of relying on Gaussian assumptions — this deals with fat-tailed shocks.
- **Upgrade to VAR-GARCH or TVP-VAR** to account for volatility clustering and evolving regimes.
- **Add global control variables** (like oil prices or US monetary shocks) to isolate the true impact of the VIX.
- **Shrink the lag structure** or apply **Bayesian/LASSO regularization** to reduce overfitting without losing dynamics.

In short, the model is informative — but still fragile. It shows us where the system bends, but not always where it breaks. Future upgrades should aim for more flexibility, especially in capturing nonlinearities and evolving risk structures.

Disclaimer: *This report is prepared solely for analytical purposes and is intended for internal use only by the Directorate General of Budget Financing and Risk Management (DJPPR), Ministry of Finance of the Republic of Indonesia. The findings and interpretations are based on statistical models applied to historical financial data. All views expressed are those of the authors and do not represent the official position of the institution.*