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May 25th 2026

Geopolitics, Geoeconomics & Risk: Different Shocks, Different Channels

A Text & Machine Learning Approach



The key Question & Results

- **Key Question: Do geopolitical & goeconomic shocks impact sovereign risk through the same transmission channels?**
 - **Answer: No!!** Both widen sovereign spreads but through different channel signatures
 - **Geopolitics Shocks:** transmit primarily through direct effect on sovereign repricing, partly offset by a Compressing Global Financial Channel (“*scissors pattern*”)
 - **Goeconomic “Uncertainty” Shocks:** increase risk mainly through Indirect channels (“*bypass the direct*”).

- **Results on Heterogeneous Geopolitical Shock effects :**
 - **Persistence:** Fundamental repricing “direct” effects *persists*; financial amplification *mean-reverts*.
 - **The Gravity Effect:** Geopolitical Direct effects decay with distance from conflict (gravity); uncertainty shocks activate globally.
 - **Originator penalty:** Geopolitical-shock originators face widening spread due to both Direct and also deteriorating Local Macro conditions.

Data & Methodology Contributions

- **From Data: The BBVA Research Database**
 - Novel daily panel (42 countries in the model) from 2018-Today using News from GDELT
 - Advanced and Emerging Markets (Asset Class Differentiation).
 - Text Indicators: Using Tone & Coverage + Local & Foreign Language

- **From the Three Layer Methodology:**
 - **Estimation: Machine Learning & Non-Linearity:**
 - Non-Linear Models Outperform.
 - News Matters for Geopolitics & Geoeconomics... the way you include them Matters too!!

 - **Interpretation: Shapley & Shaply-Taylor Decomposition:**
 - Standard: Shapley-Taylor decomposition of Geopolitics and Geoeconomics shocks.
 - Novel: Direct Effects (Shapley) and Interaction Effects (Shapley-Taylor)

 - **Validation: Standard Linear Methodologies**
 - Local Projection
 - SVAR Sign Restriction.

The BBVA Research Data

Geopolitics & Geoeconomics in Real Time



2250 Indicators
69 Countries

Geopolitics

Follow here our media sentiment indicators developed with AI techniques to analyze the global geopolitical landscape

[Geopolitics & economics](#) [Global issues](#)

Real time media sentiment indicators per country to monitor the global geopolitical landscape

Economic sentiment

It captures the sentiment and media coverage of news about the economy in the country

[Show more](#)

Economic Policy Uncertainty

It collects news about the country's economic policy uncertainty (monetary, fiscal and regulatory policies)

[Show more](#)

Trade Policy Uncertainty

Global trade faces several challenges. We disentangle between the perception to verbal and material cooperation news articles to trade

[Show more](#)

Geopolitical risk

It captures the country's geopolitical events and associated risks

[Show more](#)

Political tensions

It monitors the country's political instability, uncertainty and fragmentation

[Show more](#)

Protests

It is based on the media coverage regarding social protests or unrest in the country

[Show more](#)

Conflicts

It covers the media coverage of armed conflicts, which go beyond protests

[Show more](#)

Bilateral tensions

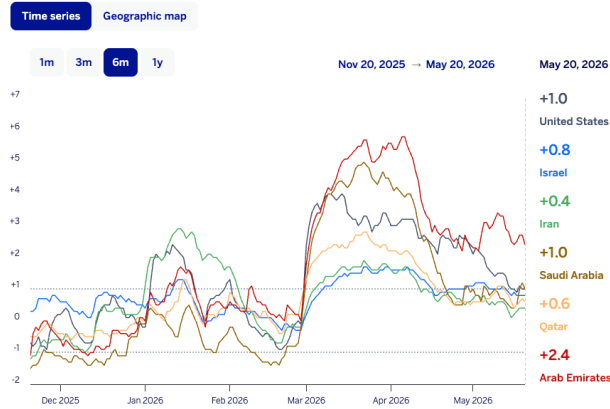
It collects news that are speaking about two countries/regions to monitor their relationship

[Show more](#)

Geopolitics and Geoeconomics Real Time

Geopolitical risk sentiment index by countries

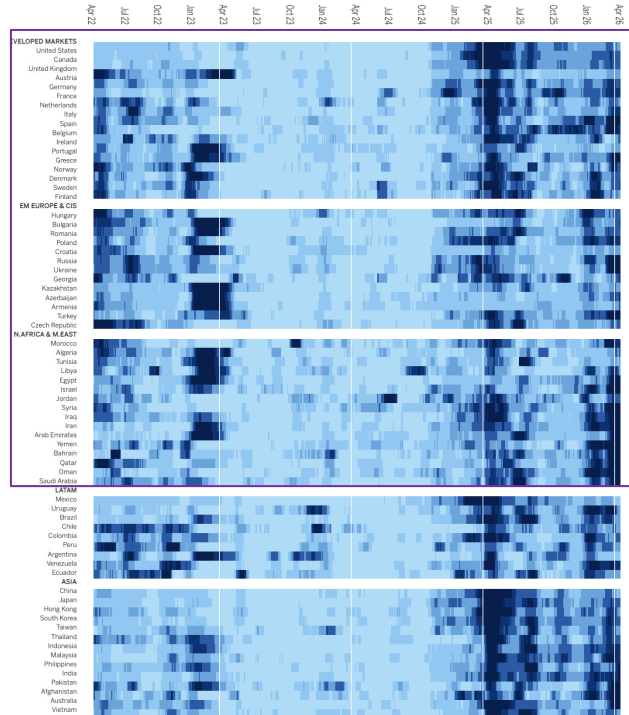
28-day weighted moving average, normalized by its own country history



Last update: May 21, 2026 | Source: BBVA Research.

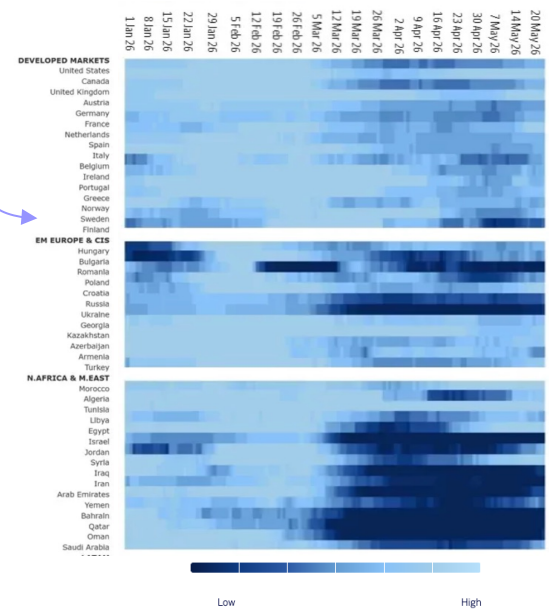
Economic Policy Uncertainty index by countries

28-day weighted moving average, normalized by its own country history



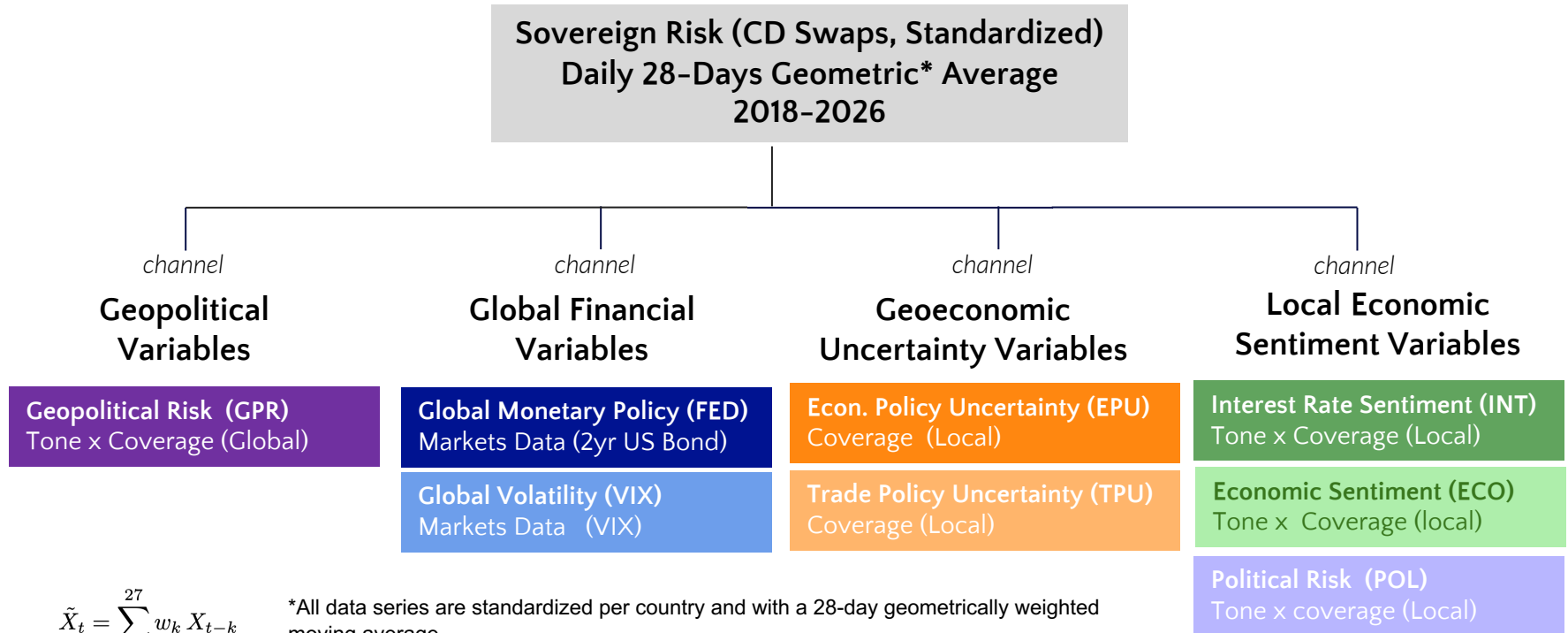
Economic sentiment index by countries

28-day weighted moving average, normalized by its own country history



Low High

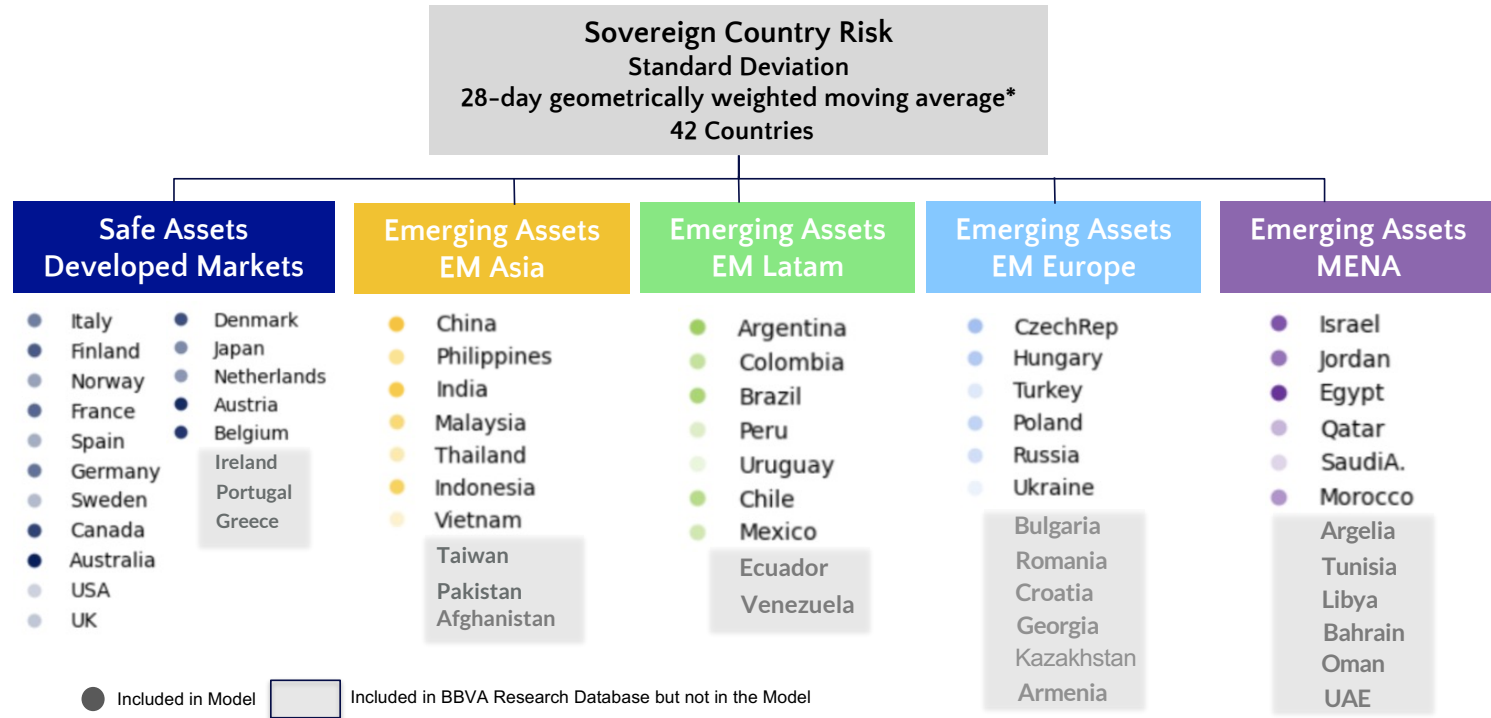
Decomposing Sovereign Risk in Geopolitics, Global Financial, Goeconomic Uncertainty and Local Macro



$$\tilde{X}_t = \sum_{k=0}^{27} w_k X_{t-k}$$

*All data series are standardized per country and with a 28-day geometrically weighted moving average.
70% of the information falls in the 1st Week ,90% in the first 2 weeks)

World Panel Sovereign Risk Model: Real Time differentiating by Asset Class (Developed & Emerging)



Methodology

The Three Layer Sequence System

Theoretical Benchmarks: What to expect from theory

Dominance Benchmarks by Shock Family Channel response

Shock family	φ^{DIR}	φ^{GFC}	φ^{UNC}	φ^{LOC}
Geopolitical (ε^G : GPR)	↑	↓ (a)		
Geoeconomic (ε^E : EPU/TPU)	$\ll \varphi_{GEO}^{DIR}$	↓ (b)	↑	↑

Direct Effect
Arellano (2008)

Default probability
conflict proximity

Global Financial
He-Khrisnamurthy (2008)
Gabaix-Maggiore (2015)

Safe-Haven flight
Demand for safe assets

Uncertainty
Pastor & Veronesi (2013)

Policy-regime beliefs
Shannon entropy

Local
Threshold Amplifiers

Domestic sentiment
fragility threshold

↑ : channel **increases spreads** — it amplifies sovereign risk
 ↓ : channel **compresses spreads**
 << : "much smaller than."

Arellano (2008): "Default Risk and Income Fluctuations in Emerging Economies" → Direct effect on default probability

He & Krishnamurthy (2013): "Intermediary Asset Pricing" → Safe-haven flight compresses GFC channel

Gabaix & Maggiore (2015): "International Liquidity and Exchange Rate Dynamics" → Financiers with limited risk capacity; higher demand for safe assets compresses sovereign discount rates globally

Pástor & Veronesi (2013): "Political Uncertainty and Risk Premia" — JFE → Uncertainty on next policy regime

Methodology: The three layer system

Layer 1 (Estimation): NonLinear Machine Learning Models

15 model classes · Pseudo-real-time OOS · Multilayer Random Forest selected

News adds 15–19% forecast improvement (nonlinear) vs. 5–9% (linear)

↓ freeze architecture

Layer 2 (Interpretation): Shapley–Taylor Channel Decomposition

$$\varphi_{i,t}^{\text{tot}} = \underbrace{\varphi_{i,t}^{ZZ}}_{\varphi^{\text{dir}}} + \underbrace{\sum_{k \in G} \varphi_{i,t}^{Zk}}_{\varphi^{\text{GFC}}} + \underbrace{\sum_{k \in U} \varphi_{i,t}^{Zk}}_{\varphi^{\text{UNC}}} + \underbrace{\sum_{k \in LUR} \varphi_{i,t}^{Zk}}_{\varphi^{\text{LOC}}}$$

↓ channel series as LP outcomes

Layer 3 (Validation): Local Projections + Sign-Restricted SVAR

Panel Local Projections

$$\Delta^h Y_{i,t+h}^{ch} = \alpha_i^h + \beta^h S_{i,t} + \gamma_p' Y_{i,t-p}^{ch} + \delta' X_{i,t} + u_{i,t+h}^h$$

AR(5) innovations · Narrative dummies ($\pm 3d$)

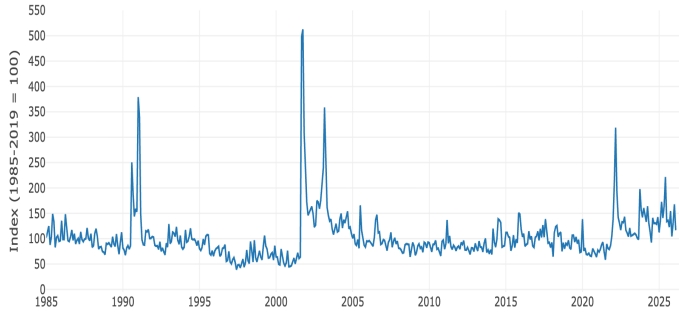
Sign-Restricted Narrative SVAR

$$Y_{i,t} = (\text{CDS}, \text{GPR}, \text{GFC}^{\text{obs}}, \text{UNC}^{\text{obs}}, \text{LOC}^{\text{obs}})'$$

Sign + magnitude + narrative (ADR-R 2018)

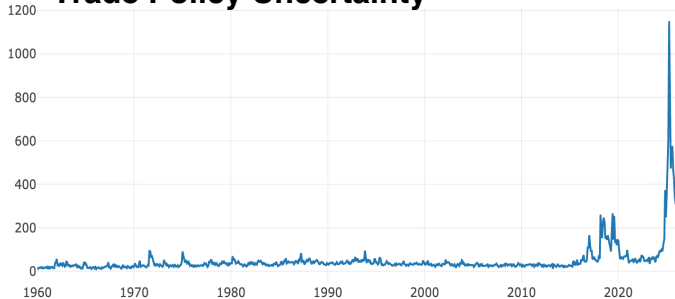
Why Nonlinear? Shocks with Spikes, Regimes & Fat Tails and misspecified estimates

Geopolitical Risk Index (GPR) Index



Caldara, Dario and Matteo Iacoviello (2022), "[Measuring Geopolitical Risk](#)," American Economic Review, April.

Trade Policy Uncertainty



Cite as: Caldara, Dario, Matteo Iacoviello, Patrick Molligo, Andrea Prestipino, and Andrea Raffo (2020), "[The Economic Effects of Trade Policy Uncertainty](#)," Journal of Monetary Economics, 109, pp.38-59.

Problems with Non-Linearity

Spikes, regime breaks, time-varying volatility, asymmetric tails...

What Linear Models Miss if you include this indicators

Estimates average across regimes · Crisis-tail effects attenuated · Country heterogeneity compressed

What Non-linear Models (or Linear Adapted) Unlock

State dependence · Crisis identification · Variable interactions · Country-specific amplification · Heterogeneity · forecast gain

Layer I : Non-Linear Machine Learning

Model Specification (Panel

$$y_{i,t+1} = f(\mathbf{X}_{i,t}, \boldsymbol{\lambda}_i) + \varepsilon_{i,t+1},$$

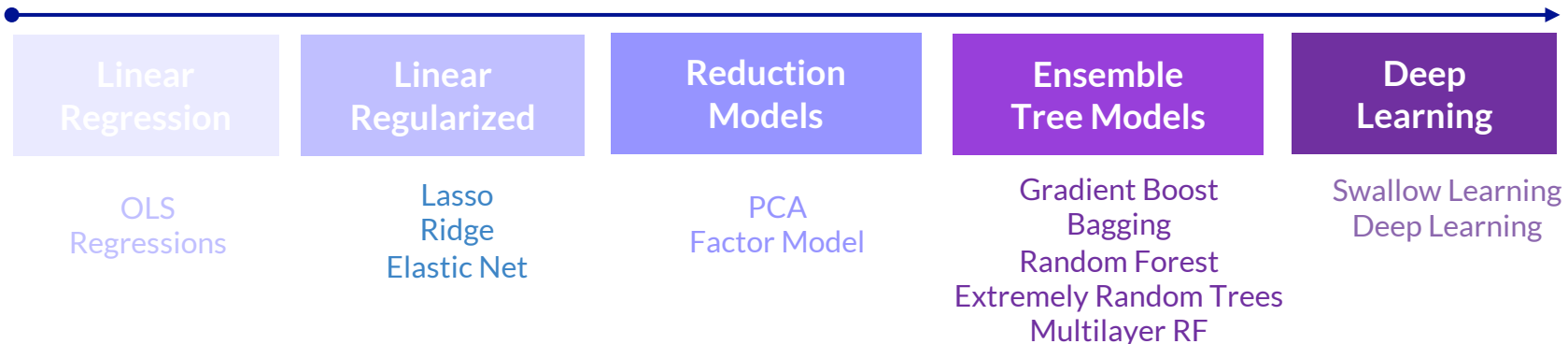
$$\hat{f}^{(m)} = \arg \min_{f \in \mathcal{F}_m} \mathcal{L}^{(m)} = \frac{1}{|\mathcal{S}|} \sum_{(i,t) \in \mathcal{S}} L(e_{i,t}^{(m)}),$$

Evaluation Metrics

$$e_{i,t+1}^{(m)} = y_{i,t+1} - \hat{y}_{i,t+1}^{(m)}, \quad (i, t) \in \mathcal{S}_{\text{roll}},$$

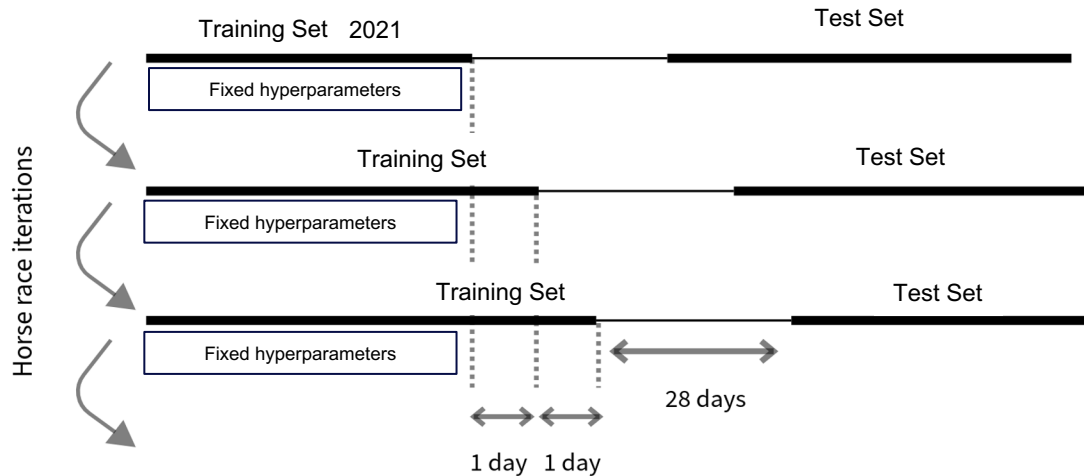
$$\text{MAE}^{(m)} = \frac{1}{|\mathcal{S}_{\text{roll}}|} \sum_{(i,t) \in \mathcal{S}_{\text{roll}}} |e_{i,t+1}^{(m)}|,$$

The Road to Complexity...



Layer I :The Horse race goal: Selecting the Best Model for Narratives (not forecasting). Avoid Leakage

Necessary Condition for ML models with Text: Avoid Train-Test Leakages
(Pseudo out of sample rolling procedure)



Avoid traditional Bias-Variance ML Problem or “Memorization” if you work with LLMs. Check for “Leakages” between Train-Test Samples

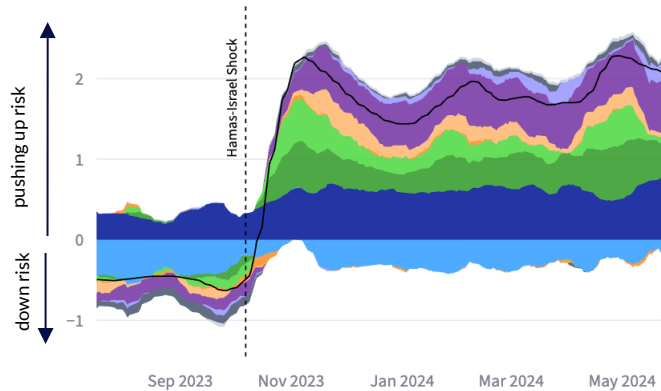
Source: Ludwig, J., Mullainathan, S and Rambachan (2025)

Layer II: Building Narratives and decomposing the Shocks through Shapley-Taylor Values

Shapley Decomposition of Explanatory Variables
(Direct & Indirect together)

$$\hat{y}_{i,t} = \underbrace{\varphi_0}_{\text{base value}} + \underbrace{\sum_{j=1}^M \varphi_{jj,i,t}}_{\text{main effects}} + \underbrace{\sum_{j < k} \varphi_{jk,i,t}}_{\text{pairwise interactions}}$$

Israel



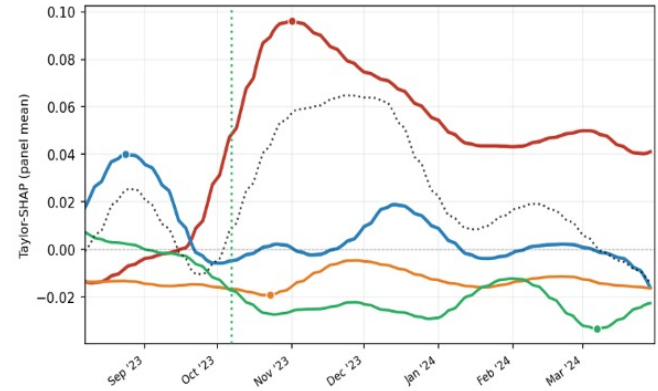
- Global Monetary Policy Rate (2Y UST)
- Economic Policy Uncertainty (EPU)
- Global Financial Volatility (VIX)
- Trade Policy Uncertainty (TPU)
- Local Interest Rate Sentiment
- Geopolitical Risk Index (GPR)
- Local Economic Sentiment
- Political Tensions Index (POL)

Inside the Shock
(direct & Indirect effect)

Shap-Taylor Decomposition
(i.e Geopolitics) in Direct & Interaction Effects

$$\underbrace{\varphi_{i,t}^{Z,tot}}_{\text{total}} = \underbrace{\varphi_{ZZ,i,t}}_{\varphi_{i,t}^{Z,dir}} + \underbrace{\sum_{k \in \mathcal{G}} \varphi_{Zk,i,t}}_{\varphi_{i,t}^{Z,GFC}} + \underbrace{\sum_{\substack{k \in \mathcal{U} \\ k \neq Z}} \varphi_{Zk,i,t}}_{\varphi_{i,t}^{Z,UNC}} + \underbrace{\sum_{\substack{k \in \mathcal{L} \cup \mathcal{R} \\ k \neq Z}} \varphi_{Zk,i,t}}_{\varphi_{i,t}^{Z,LOC}}$$

b) Hamas-Israel (Oct 2023)



- Direct Effect
- Global Financial
- Economic Uncertainty
- Local Macro & Politics

Layer III: SVAR Identification of the Shocks through theoretical priors

Table 11: SVAR Sign Restrictions Implied by the Semistructural Framework

Variable	Geopolitical shock (ε^G)		Geoeconomic shock (ε^E)	
	$h=0$	$h=5$	$h=0$	$h=5$
$CDS_{i,t}$	+	+		
$GPR_{i,t}$ (Direct)	+	+	≈ 0	≈ 0
GFC_t^{obs}	-	-	-	-
$UNC_{i,t}^{obs}$			+	+
$LOC_{i,t}^{obs}$			+	+

Table 6: Cross-Validation Summary Across Methods

Figure / section	Method	Variables	Result	Relation to baseline
Main text	Shapley $\Delta_{1,m}$ + narrative LP	ML channels	16/16 event-channel predictions	Baseline
Appendix Figure 16	Sign-restricted SVAR	ML channels	8/8 sign and magnitude relations	Internal coherence
Figure 8	Sign-restricted mean-group SVAR	Raw observables	8/8 sign and magnitude relations	Independent of ML decomposition
Appendix Figure 17	Full-sample LP with identified SVAR shocks	Raw observables	Null average responses	Consistent with state dependence

Notes: “Result” reports the number of predicted sign and relative-magnitude relations supported by the baseline posterior median. “Independent of ML decomposition” means that the raw-observable SVAR neither estimates nor identifies shocks using Shapley–Taylor values. “Null average responses” means that the full-sample LP responses are economically small and statistically indistinguishable from zero at conventional levels.

Empirical Results

ML Horse Race: Nonlinear Models superior out-of-sample and Unlock the Predictive Content of News

Table 2: News Indicators Improve Nonlinear Forecasts of Sovereign Risk

Machine Learning Model	Benchmark Market Only		News Extended Market + News		Difference (News Extended vs Benchmark)			
	RMSE	MAE	RMSE	MAE	RMSE		MAE	
					Diff	% Var	Diff	% Var
Linear Regression	1.09	0.92	1.03	0.86	-0.06	-5.7%	-0.06	-6.4%
Lasso	1.03	0.87	0.95	0.80	-0.08	-8.0%	-0.08	-8.7%
Ridge	1.09	0.92	1.02	0.85	-0.07	-6.4%	-0.07	-7.2%
Elastic Net	1.04	0.88	0.95	0.79	-0.09	-8.8%	-0.08	-9.5%
Quantile Linear Regression	0.93	0.77	0.90	0.74	-0.03	-3.7%	-0.03	-4.5%
Principal Components (PCR)	1.09	0.92	0.99	0.82	-0.09	-8.6%	-0.09	-10.3%
Factor Models (FAR)	0.92	0.75	0.88	0.72	-0.04	-4.4%	-0.03	-3.6%
Gradient Boosting	1.00	0.81	0.85	0.67	-0.14	-14.2%	-0.14	-17.9%
Bagging	1.03	0.83	0.84	0.67	-0.19	-18.3%	-0.17	-20.1%
Random Forest	0.99	0.75	0.82	0.65	-0.17	-17.1%	-0.11	-14.3%
Extremely Randomized Trees	0.98	0.74	0.80	0.60	-0.18	-18.5%	-0.14	-19.0%
Multilayer Random Forest (1S)	0.97	0.75	0.84	0.62	-0.13	-13.6%	-0.13	-17.2%
Multilayer Random Forest (2S)	1.01	0.77	0.85	0.65	-0.16	-15.9%	-0.12	-15.5%
Shallow CNN	1.05	0.84	0.97	0.77	-0.09	-8.3%	-0.07	-8.8%
Deep CNN	1.04	0.77	0.89	0.66	-0.15	-14.1%	-0.11	-14.3%

Notes: Out-of-sample RMSE and MAE for one-day-ahead forecasts of standardized sovereign CDS spreads under two information sets: Markets-Only (VIX and U.S. two-year Treasury yield) and Markets+News (augmented with GPR, EPU, TPU, ECO, INT, POL). All variables are 28-day moving averages. Models are estimated recursively with a 28-day exclusion buffer. "Diff" denotes the change relative to the Markets-Only benchmark; negative values indicate lower forecast loss.

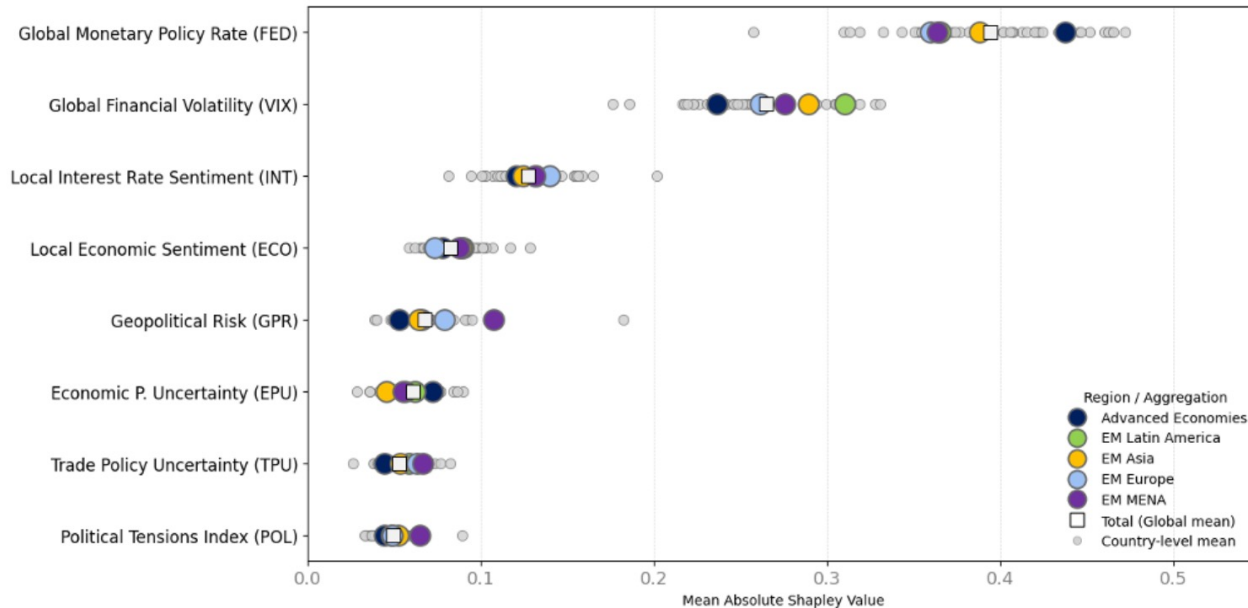
Key finding: News variables improve *all* model classes, but gains are **3× larger** for nonlinear methods.

- ▶ Linear models: 5–9% RMSE reduction
- ▶ Tree ensembles: **15–19%** RMSE reduction
- ▶ Best: Extremely Randomised Trees (MAE = 0.60)
- ▶ Baseline for interpretation: **Multilayer Random Forest (2S)** — preserves AE/EM split

⇒ Predictive content of news enters through *interactions* and *threshold effects*

What Drives Sovereign Risk? Global Finance Dominates Geopolitics & Geoeconomic works through Interactions

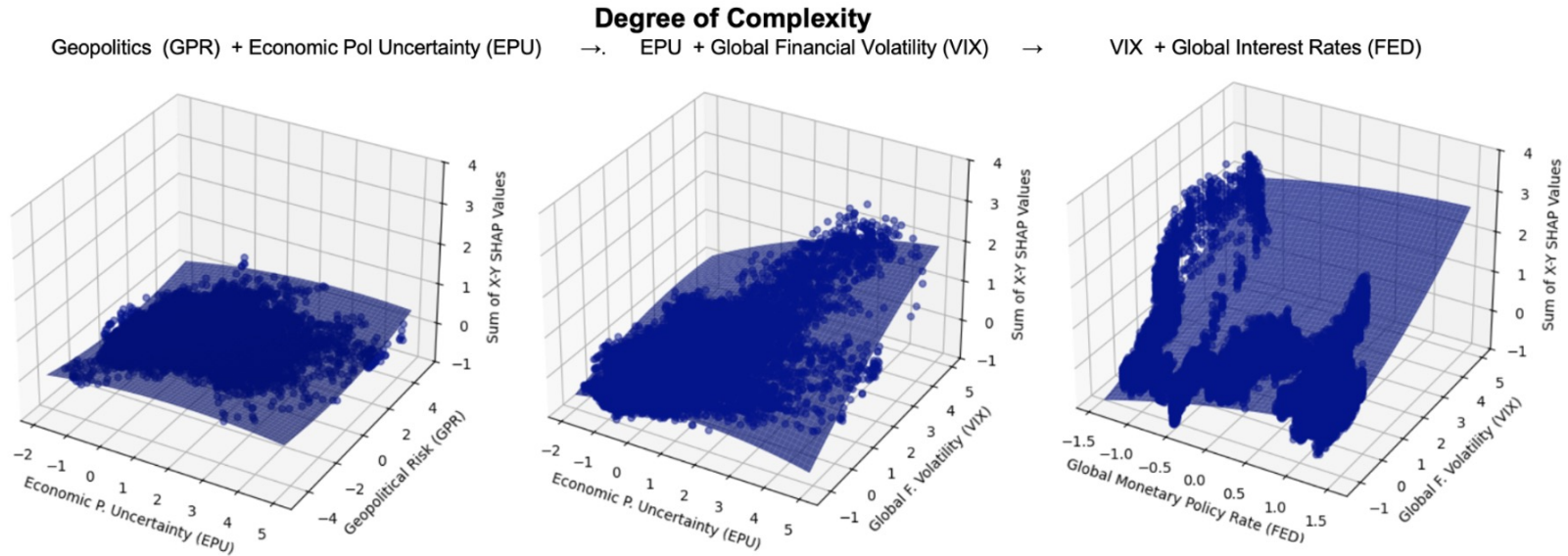
Figure 1: Global Financial Conditions Dominate Sovereign Risk: Shapley Feature Importance



Notes: Mean absolute Shapley values for all predictors over 2018–2025, shown at the global, regional, and country levels. Country-level values are computed by averaging over all observations for each country; the global value is the unweighted mean across country means.

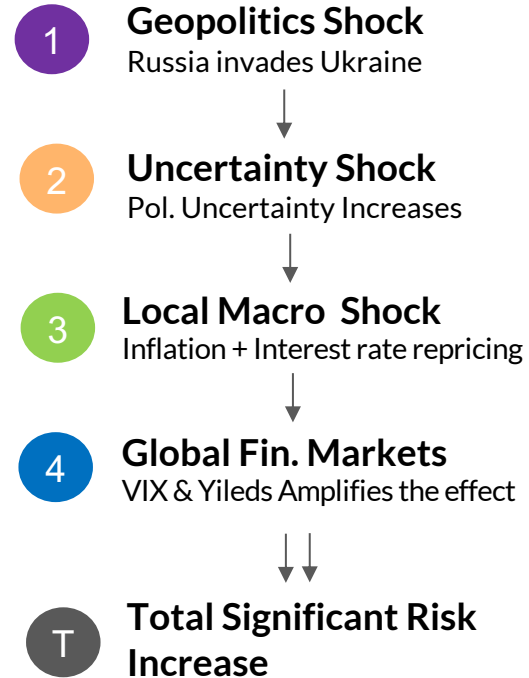
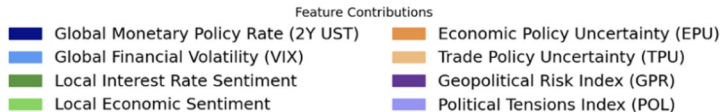
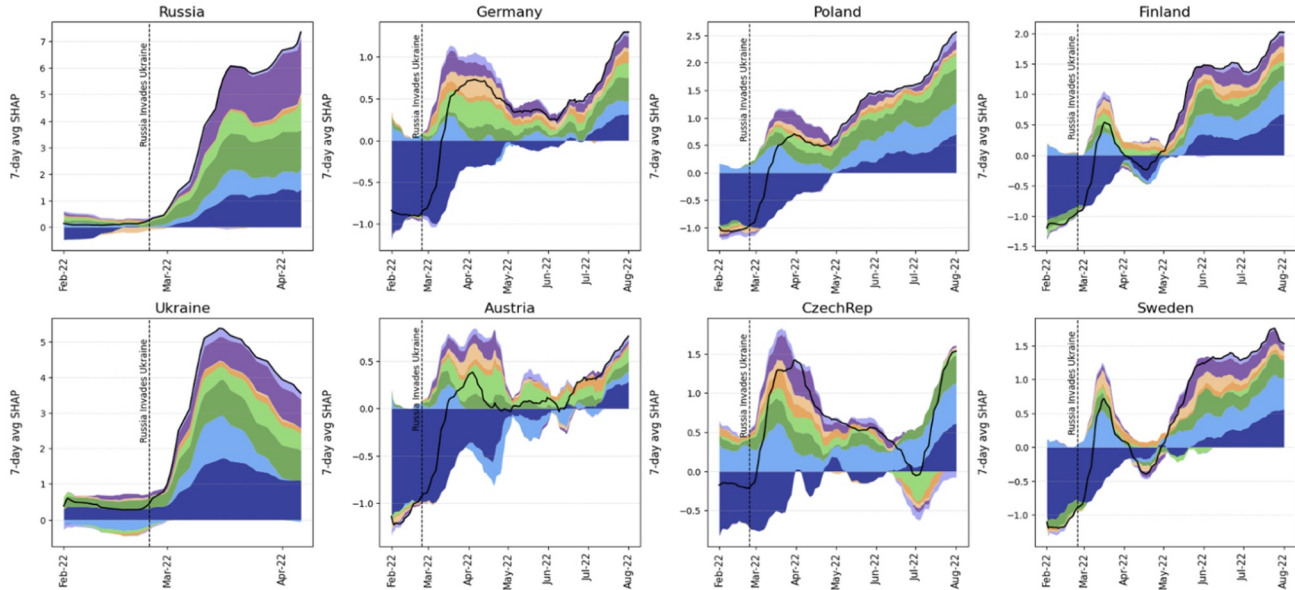
Geopolitics is State Dependent: Small in Isolation, Powerful in Interaction with Global Financial Markets

Figure 2: State Dependence in Sovereign Risk: Two-Factor Interaction Surfaces

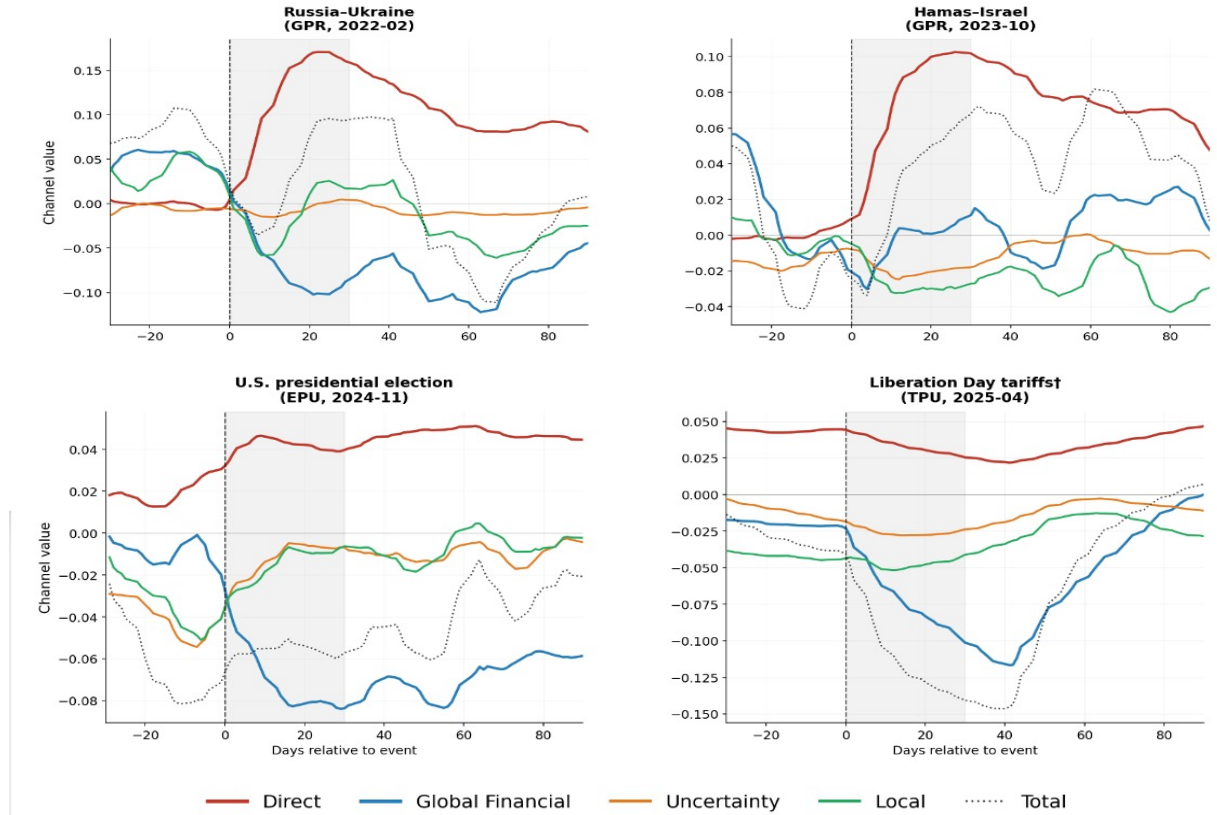


How Geopolitical Shock can morph in a Systemic Financial Crisis (Sequence During Russia-Ukraine event)

Sovereign risk after the Russian-Ukraine Invasion (2022)

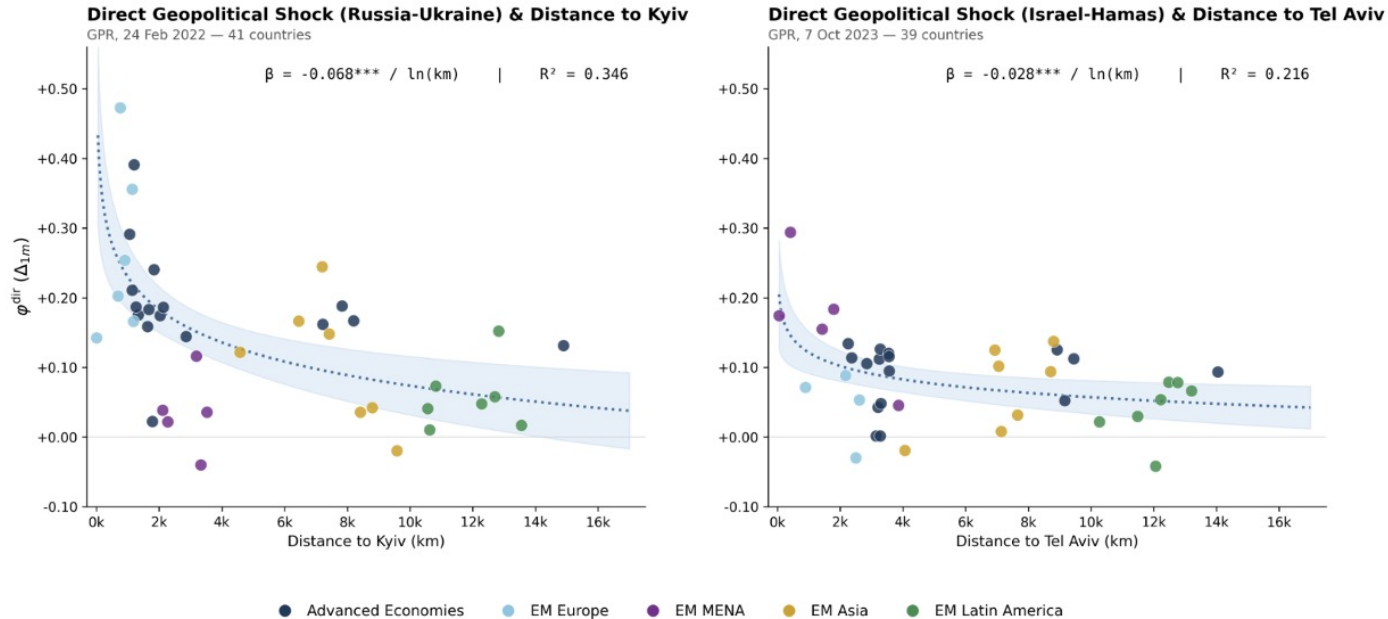


The Scissors: Geopolitics Re-prices Directly while Geoeconomics Transmits via Uncertainty & Local



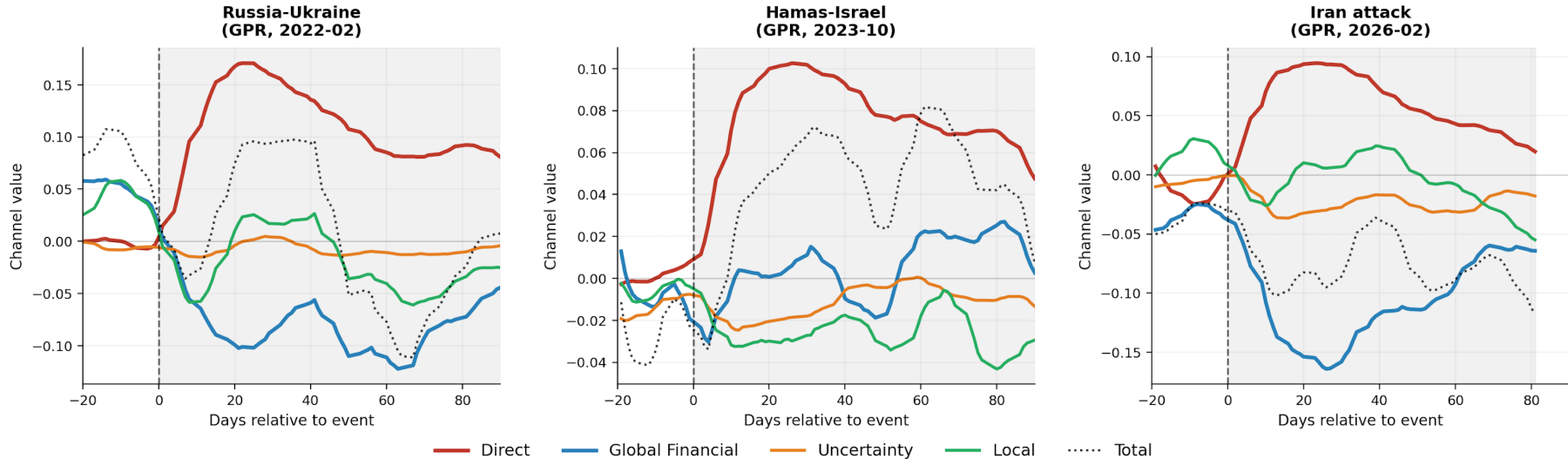
Gravity in Sovereign Risk: Direct Effects Decay with Distance from Conflict

$$\varphi_i^{\text{dir}} = \alpha + \beta \ln d_i + u_i$$



Does the Scissor Effect hold during the US-Israel-Iran conflict? ... Indeed

Sovereign risk after alternative Geopolitical Shocks: The “Scissor Patterns”
(Direct Negative Geopolitical effect compensated with Positive effects from Global Financial)

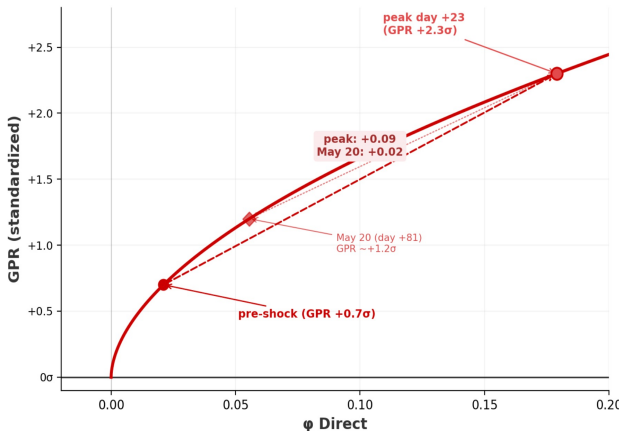


Notes: Cross-sectional average of the four Shapley–Taylor transmission channels for GPR shocks. Direct (red): own Shapley–Taylor term. Global Financial (blue): interactions with VIX and US2Y. Uncertainty (orange): interactions with EPU and TPU. Local (green): interactions with ECO, INT, POL, and REG. Dotted black line: total Shapley contribution. Vertical dashed lines mark the event date. All series are 7-day moving averages with a trailing smoother. Iran panel limited to available data window.

And how the Scissor Pattern worked (again) during the US-Israel-Iran conflict?

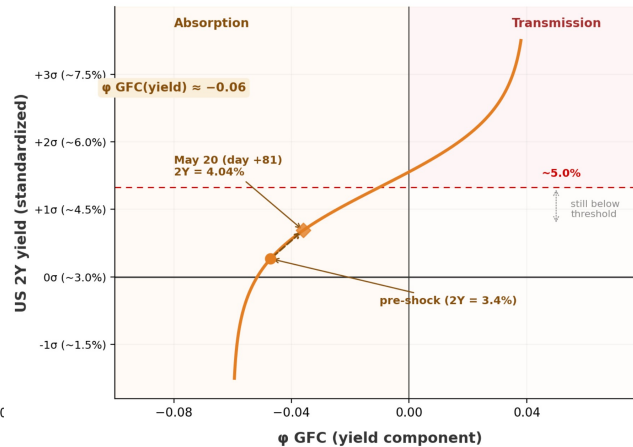
The Negative Direct effect has been similar to past geopolitical events –
And VIX and Global yields (US 2Y Treasury bill) stayed in the absorption zone.

A) Direct Effect — Iran attack



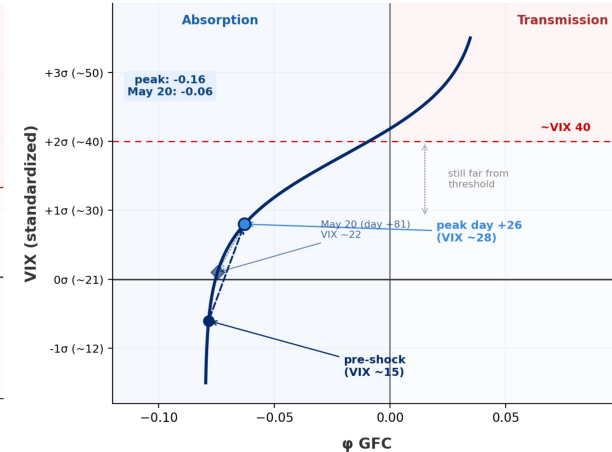
GPR elevated → activation → dissipating by May 20

B) Global Yields (US2Y) — Iran attack



Yields rise from 3.4% to 4.04% — still in absorption, below ~5.0% threshold

C) VIX — Iran attack



VIX rises then retreats — always in absorption zone, never near ~40

Structural sign Restrictions-SVAR shows recover the Geopolitics scissor & Geoeconomic bypass results

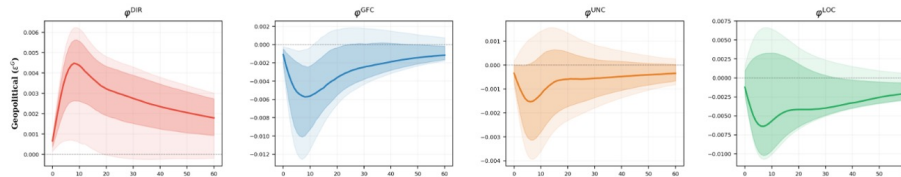
Dominance Benchmarks by Shock Family

Channel response

Shock family	φ^{DIR}	φ^{GFC}	φ^{UNC}	φ^{LOC}
Geopolitical (ε^G : GPR)	↑	↓ (a)		
Geoeconomic (ε^E : EPU/TPU)	≪ φ^{DIR}_{GEO}	↓ (b)	↑	↑

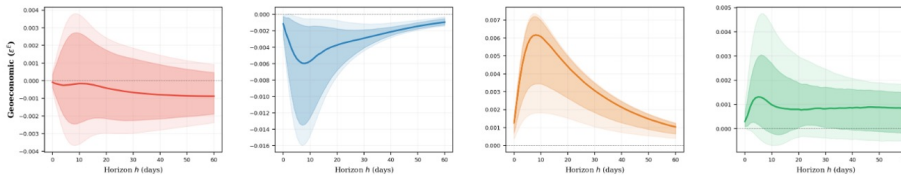
Structural IRFs – Narrative Sign-Restricted SVAR (VAR(5), 617 accepted draws, 4 narrative events)

Geopolitics Shock



Geopolitical shocks transmit primarily through direct sovereign repricing, partly offset by a compressing Global Financial Cycle channel (“scissors pattern”)

Geoeconomics
Uncertainty Shock



Geoeconomic shocks bypass the Direct channel and transmit mainly through financial conditions, policy uncertainty, and domestic amplification (“bypassing direct”)

Notes: Mean-group structural impulse responses from country-level VAR(5) models estimated on the four Shapley–Taylor channel series (φ^{DIR} , φ^{GFC} , φ^{UNC} , φ^{LOC}), identified with sign restrictions (Table 11), relative-magnitude restrictions, and narrative restrictions on four crisis dates following Antolin-Diaz and Rubio-Ramirez (2018). Top row: geopolitical shock (ε^G); bottom row: geoeconomic shock (ε^E). Solid lines: posterior median across 617 accepted draws. Dark shaded bands: 68% pointwise credible intervals; light bands: 90%. The geopolitical shock raises φ^{DIR} while φ^{GFC} falls, reproducing the scissors pattern. The geoeconomic shock produces a muted and eventually negative φ^{DIR} , with the GFC, Uncertainty, and Local channels carrying transmission. All eight sign and dominance predictions are confirmed at the postmedian. Because this system uses Shapley–Taylor values as inputs, it serves as an internal coherence check rather than an independent validation; Figure 16 provides the independent test on raw observables.

Policy Implications

- **Enhancing the Policy Toolbox of Geopolitics and Geoeconomic Indicators & Analysis**
 - Real Time Database to monitor Geopolitics and Geoeconomics
 - Decomposition → Direct and Indirect effects matters
- **Policy implication:**
 - **Direct sovereign repricing → liquidity tools insufficient;** requires diplomatic de-escalation, institutional strengthening or fiscal policies to tackle the negative effects.
 - **Global Financial Channel -mediated widening → addressable via central-bank liquidity.**

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Appendix

Related Literature

- **Machine Learning & News-based risk measurement**
 - ML in economics: Athey & Imbens (2019), Mullainathan & Spiess (2017), Gu, Kelly & Xiu (2020)
 - GPR: Caldara & Iacoviello (2022); EPU: Baker, Bloom & Davis (2016); TPU: Caldara et al. (2020)
 - Local-language sources outperform Anglosphere media: Bondarenko et al. (2024), Alonso-Alvarez et al. (2025)
 - We confirm News “value” and the Power on Non-Linear Models for Geopolitical & Goeconomic News

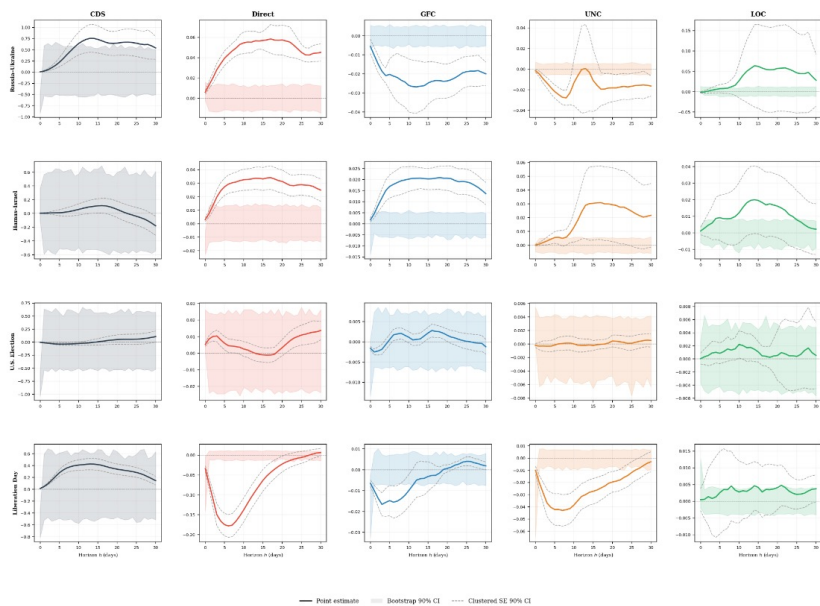
- **Sovereign risk, geopolitics & goeconomic statecraft**
 - Geopolitical risk widens spreads: Fernández-Villaverde et al. (2024), Boubaker et al. (2023)
 - Trade tensions amplify uncertainty: Ahn & Ludema (2020), Aiyar et al. (2023)
 - Sovereign CDS reflect default + global risk-premium components: Longstaff et al. (2011), Augustin et al. (2022)
 - Goeconomic vulnerability & leverage: Clayton, Maggiori & Schreger (2026 *Econometrica*)
 - We show geopolitical and goeconomic shocks operate through qualitatively different channels

- **Global Financial Cycle & international asset pricing**
 - Common factor in cross-border prices: Rey (2013), Bruno & Shin (2015), Miranda-Agrippino & Rey (2020)
 - Sovereign risk-premium, dollar funding, safe-haven flows: Longstaff et al. (2011), Du et al. (2018), Bahaj & Reis (2022), Maggiori et al. (2020)
 - We show the GFC channel does not respond uniformly: scissors under geopolitical shocks; dominant transmission margin under goeconomic shocks

Bootstrap: Addressing the generated-regressor problem

Figure 20: **Block Bootstrap Validation of Narrative LP Impulse Responses** ($B = 500$, 4 narrative events)

Appendix Figure 19: Generated-Regressor Block Bootstrap ($B = 500$, 4 events)



Placebo: Are these channel responses exceptional or can we see similar patterns on random dates?

Figure 16: Placebo Test (GPR): Russia–Ukraine, Feb. 24, 2022

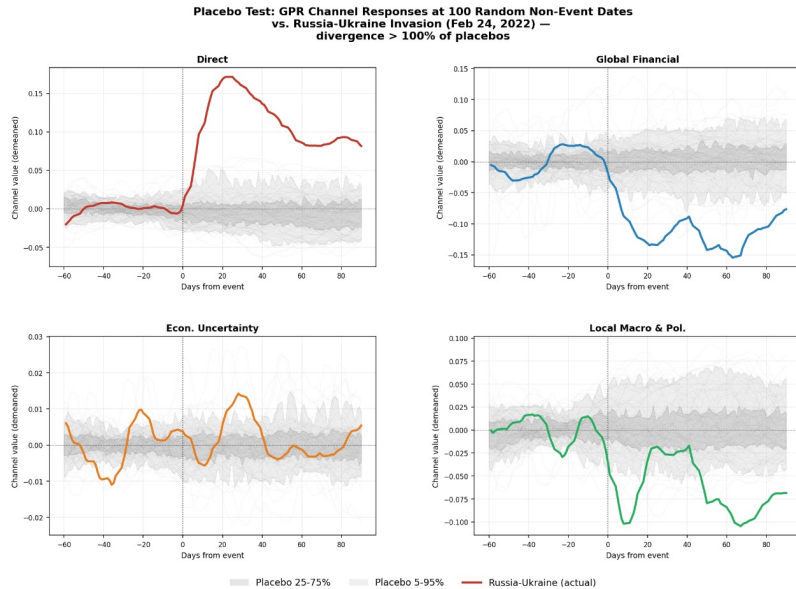
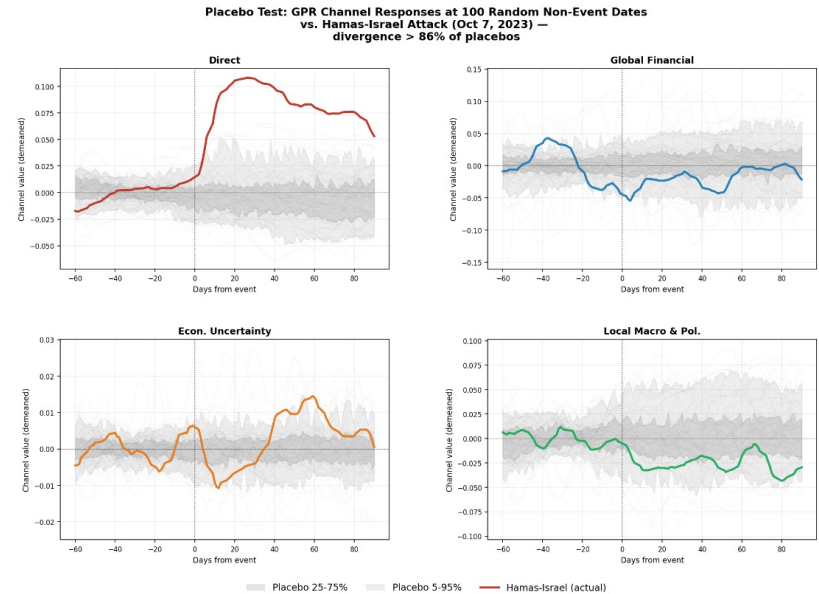
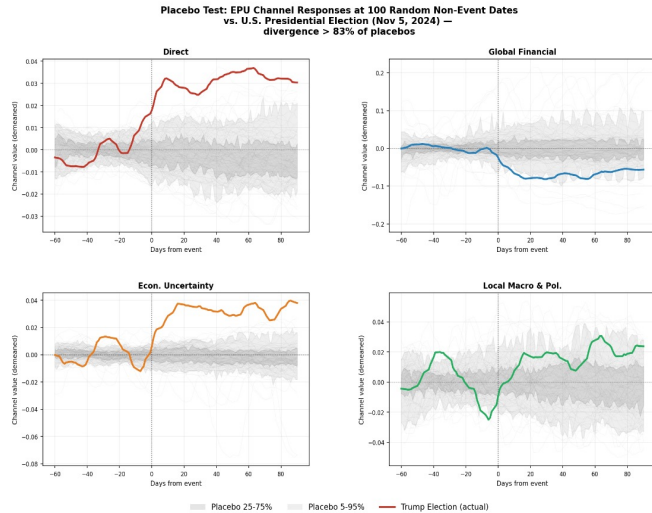


Figure 17: Placebo Test (GPR): Hamas–Israel, Oct. 7, 2023 — Divergence > 86% of Placebos



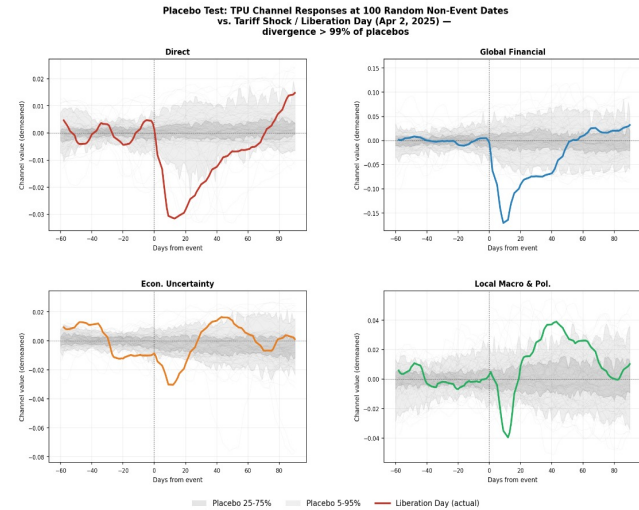
Placebo: Are these channel responses exceptional or can we see similar patterns on random dates?

Figure 18: Placebo Test (EPU): U.S. Presidential Election, Nov. 5, 2024 — Divergence > 83% of Placebos



Notes: The Uncertainty channel exits the envelope upward after day 0, consistent with EPU-driven repricing. The GFC channel drops below the band. The Direct channel rises modestly above the envelope, reflecting tariff-related repricing accompanying the election. 25–75% (dark) and 5–95% (light) placebo bands from 100 random non-event dates. 7-day trailing MA; values demeaned over the pre-event window.

Figure 19: Placebo Test (TPU): Liberation Day Tariff Shock, Apr. 2, 2025 — Divergence > 99% of Placebos



Notes: The GFC channel collapses below the envelope immediately after day 0—the largest single-channel departure across all four episodes. The Direct channel moves *negative*, consistent with the taxonomy’s prediction that tariff shocks bypass conflict-proximity repricing. The Local channel exits upward, reflecting heterogeneous tariff exposure. 25–75% (dark) and 5–95% (light) placebo bands from 100 random non-event dates. 7-day trailing MA; values demeaned over the pre-event window.

Layer III: Do the Shapley-Taylor Channels Respond to the Right Shocks? (LP Validation)

$$\Delta_h Y_{i,t+h}^{ch} = \alpha_i^h + \beta^h S_{i,t} + \sum_{p=1}^5 \gamma_p^h Y_{i,t-p}^{ch} + \delta^{h'} \mathbf{X}_{i,t} + u_{i,t+h}^h,$$

{ φ^{dir} , φ^{GFC} , φ^{UNC} , φ^{LOC} }

Strategy I: Full-Sample Innovation Identification

Country Specific Average Marginal Response to one standard deviation

We identify shocks as innovations from country-specific AR(5) processes:

$$Z_{i,t} = \mu_i + \sum_{p=1}^5 \rho_{i,p} Z_{i,t-p} + \varepsilon_{i,t}^Z \quad \longrightarrow \quad S_{i,t}^Z = \hat{\varepsilon}_{i,t}^Z / \hat{\sigma}_{\varepsilon,i}$$

Strategy II: Narrative Identification

Common across countries for a given event (4 individual Events)

We construct event dummies equal to one in a ± 3 -day window around each of four dated events:

$$D_t^e = \mathbf{1}\{|t - t_e| \leq 3\}, \quad e \in \{E1, E2, E3, E4\},$$

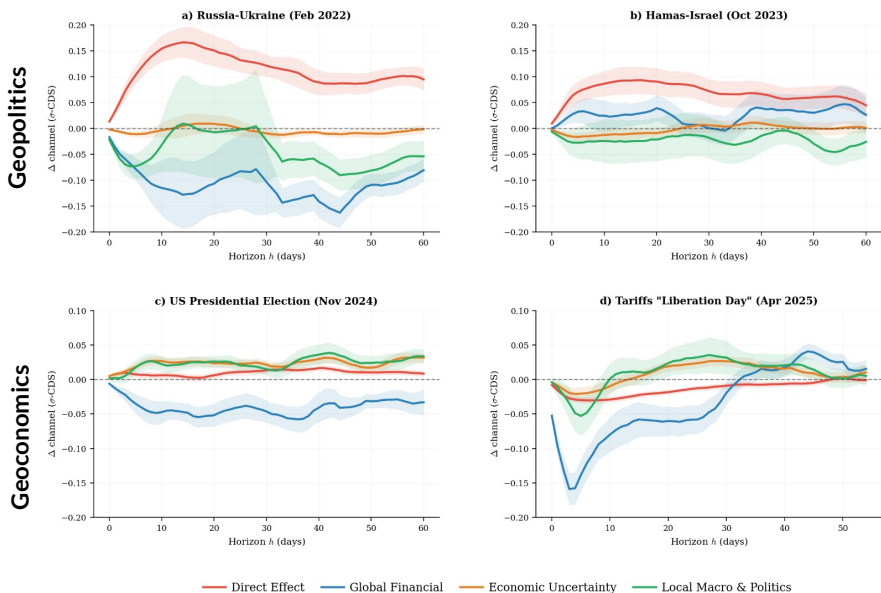
We construct event dummies equal to one in a ± 3 -day window around each of four dated events:

$$D_t^e = \mathbf{1}\{|t - t_e| \leq 3\}, \quad e \in \{E1, E2, E3, E4\}, \quad (6)$$

where $t_{E1} = 24$ February 2022 (Russia–Ukraine invasion), $t_{E2} = 7$ October 2023 (Hamas–Israel attack), $t_{E3} = 5$ November 2024 (U.S. presidential election), and $t_{E4} = 2$ April 2025 (“Liberation Day” tariff announcement). A separate local projection is estimated for each event, with $S_{i,t} = D_t^e$. Each event is paired with its primary news indicator: GPR for $E1$ and $E2$, EPU for $E3$, TPU for $E4$.

Layer III: Local projection of Shocks. Watch out with full sample AR-5 shocks focus on events

Figure 5: Channel Impulse Responses from Narrative Local Projections



Notes: Each panel plots cumulative impulse responses of the four Shapley–Taylor channels—Direct (φ^{dir} , red), GFC (φ^{GFC} , blue), Uncertainty (φ^{UNC} , orange), and Local (φ^{LOC} , green)—from narrative local projections with ± 3 -day event dummies at horizons $h = 0, \dots, 60$ days. Specification (B): VIX and US2Y controls; country FE; Driscoll–Kraay SE. Shaded bands: 90% confidence intervals.

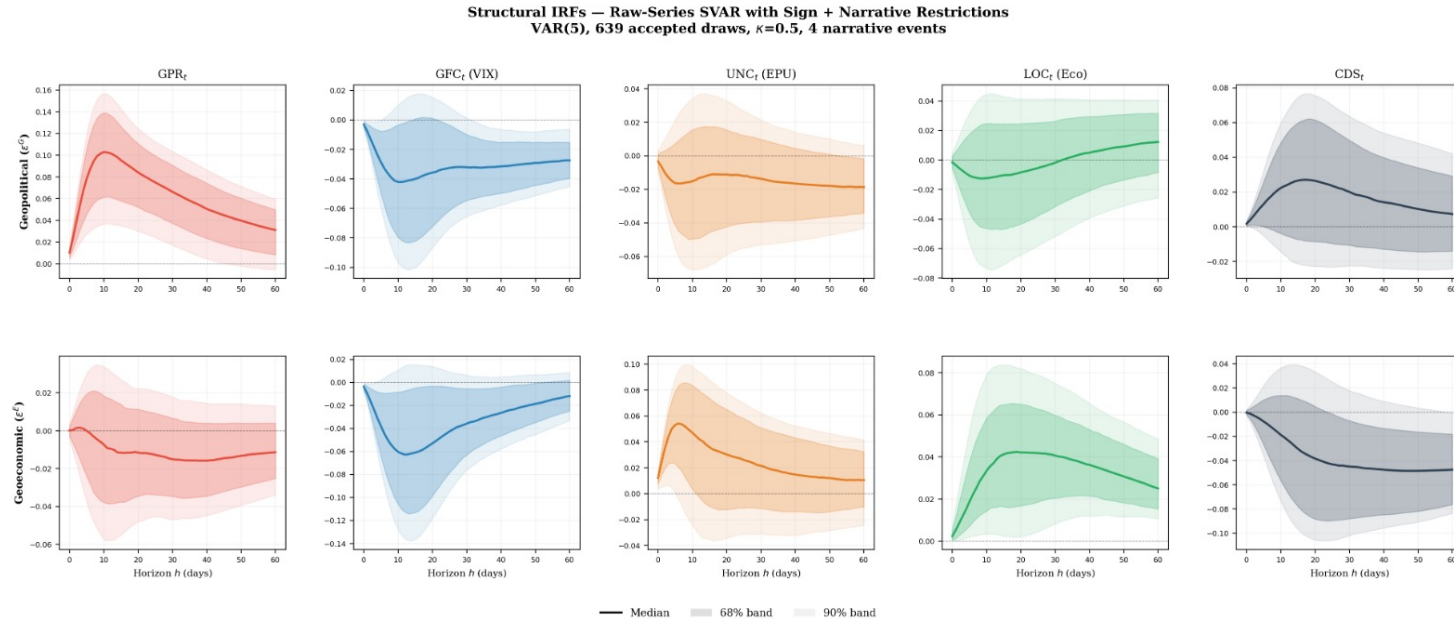
Table 5: Local-Projection Validation of the Channel Taxonomy

Episode	Channel	FULL-SAMPLE INNOVATION LP			NARRATIVE LP		
		(A)	(B)	(C)	(A)	(B)	(C)
		Baseline	Global	Extended	Baseline	Global	Extended
Russia–Ukraine GPR, Feb. 2022 <i>Geopolitical</i>	φ^{dir}	+ .005 –	+ .005 –	+ .005 –	+ .122 ***	+ .121 ***	+ .125 ***
	φ^{GFC}	– .001 –	– .001 –	– .001 –	– .102 ***	– .104 ***	– .102 ***
	φ^{UNC}	– .000 –	– .000 –	– .000 –	– .009 *	– .010 *	– .009 **
	φ^{LOC}	– .004 –	– .004 –	– .004 –	– .018 –	– .023 –	– .023 –
Hamas–Israel GPR, Oct. 2023 <i>Geopolitical</i>	φ^{dir}	+ .005 –	+ .005 –	+ .005 –	+ .071 ***	+ .072 ***	+ .068 ***
	φ^{GFC}	– .001 –	– .001 –	– .001 –	+ .003 –	+ .000 –	– .000 –
	φ^{UNC}	– .000 –	– .000 –	– .000 –	+ .006 –	+ .006 –	+ .006 –
	φ^{LOC}	– .004 –	– .004 –	– .004 –	– .017 –	– .018 –	– .019 –
U.S. Election EPU, Nov. 2024 <i>Geoeconomic</i>	φ^{dir}	+ .002 –	+ .002 –	+ .003 –	+ .013 ***	+ .013 ***	+ .015 ***
	φ^{GFC}	+ .002 –	+ .002 –	+ .004 –	– .046 ***	– .046 ***	– .046 ***
	φ^{UNC}	+ .001 –	+ .001 –	+ .001 –	+ .021 ***	+ .021 ***	+ .024 ***
	φ^{LOC}	+ .000 –	+ .000 –	+ .000 –	+ .016 ***	+ .015 ***	+ .017 ***
“Liberation Day” TPU, Apr. 2025 <i>Geoeconomic</i>	φ^{dir}	– .001 –	– .001 –	– .002 –	– .008 ***	– .009 ***	– .016 ***
	φ^{GFC}	– .001 –	– .001 –	– .001 –	– .015 –	– .019 *	– .028 ***
	φ^{UNC}	+ .001 –	+ .001 –	+ .001 –	+ .026 ***	+ .026 ***	+ .034 ***
	φ^{LOC}	+ .000 –	+ .000 –	– .001 –	+ .034 **	+ .032 **	+ .023 *

Notes: Each cell reports the cumulative impulse response at horizon $h = 30$ days. Coefficients rounded to three decimal places. *Full-sample innovation LP*: panel local projection with country-specific AR(5) innovations; Driscoll–Kraay SE with bandwidth $\max(20, h)$, country and time FE, 5 lags. *Narrative LP*: panel local projection with ± 3 -day event dummies; Driscoll–Kraay SE with country FE. Controls: (A) none; (B) VIX, US2Y; (C) VIX, US2Y, ECO, INT, POL, EPU, TPU. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$; – = not significant at 10%. Cell shading indicates significance level of the Narrative LP estimate: $p < 0.01$, $p < 0.05$, $p < 0.10$. Because the full-sample innovation LP is estimated by shock type rather than by narrative episode, the GPR-based coefficients are repeated in the two geopolitical rows to facilitate comparison with the narrative panel. GPR = Geopolitical Risk, EPU = Economic Policy Uncertainty, TPU = Trade Policy Uncertainty, US2Y = U.S. two-year Treasury yield.

Layer III : Sign Restrictions-SVAR shows Geopolitics scissor & Geoeconomic bypass recoverable from raw data

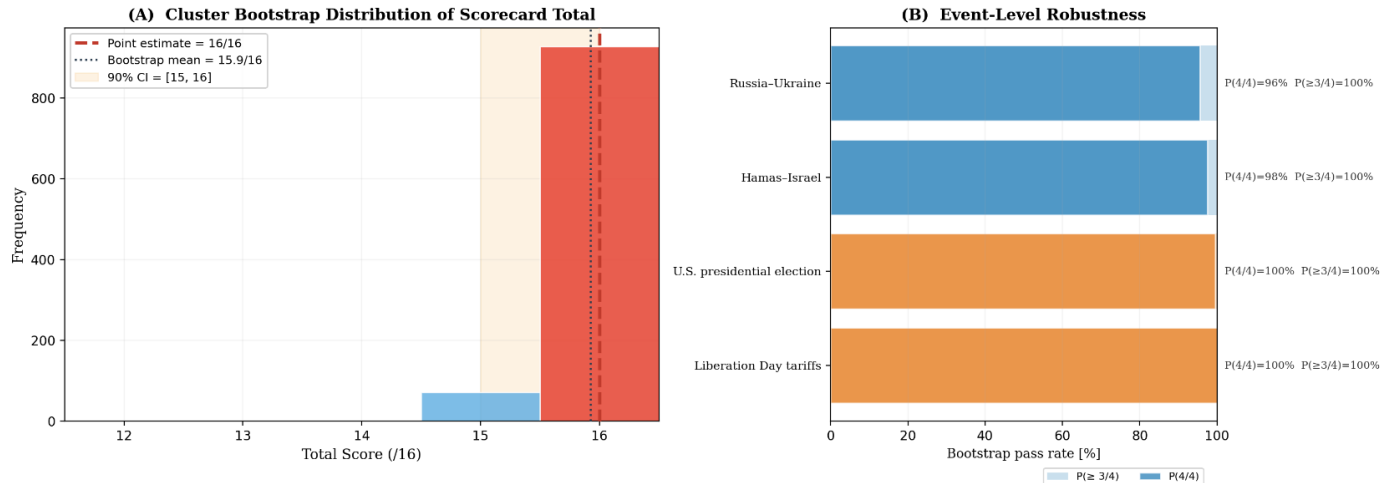
Figure 22: Narrative Sign-Restricted SVAR: Structural Impulse Responses on Raw Observables



Is the 100% scorecard validation robust to the cross-sectional panel, or does it depend on a few countries?

Figure 8: Cluster Bootstrap Validation of Taxonomy of Events

(a) 1000 replications, resampling 42 countries with replacement



Notes: Each of B = 1,000 replications resamples 42 countries with replacement from the original panel, recomputes the cross-country daily panel mean of each Shapley-Taylor channel, and re-scores the 1-event taxonomy. Point estimate: 16/16. Bootstrap mean: 15.9/16 (sd = 0.3). 90% CI: [15, 16]. Panel (B) dark bars show P(4/4); light bars show P(≥ 3/4). Values report P(4/4) | P(≥ 3/4).

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May 25th 2026

Geopolitics, Geoeconomics & Risk: Different Shocks, Different Channels

A Text & Machine Learning Approach

