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Institutional Channels of Geopolitical Risk Transmission to Foreign Exchange Volatility Mixed-Frequency Models and Externally Instrumented Local Projections

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***Abstract*—Why do geopolitical risk shocks propagate with four to five times greater force to emerging-market currencies than to developed-market currencies? We develop a theoretical model showing that the exchange rate variance response to geopolitical risk is inversely proportional to a country's composite institutional buffer—comprising central bank independence, reserve adequacy, and the foreign-currency debt burden—and test this prediction using a unified four-model econometric strategy. As the primary estimation framework, GARCH-MIDAS-X models correctly handle the mixed-frequency mapping from monthly geopolitical risk to daily exchange rate returns, overcoming the temporal aggregation bias in prior GARCH-X studies. A heterogeneous autoregressive realised volatility (HAR-RV) panel with continuous institutional interaction terms provides the primary cross-country evidence. For identification, we construct a geographic distance- and trade-adjusted external geopolitical risk instrument—a Bartik-type measure that isolates globally transmitted geopolitical shocks orthogonal to each country's domestic macroeconomic conditions—and embed it within two-stage local projections (2SLS-LP). The first-stage F-statistic of 18.4 indicates a strong instrument; 2SLS-LP impulse responses are virtually identical to OLS-LP responses, allaying reverse-causality concerns for the average currency pair. Applying the Perron-Qu (2010) test to discriminate genuine long memory from structural-break-induced spurious persistence, we confirm fractional integration d > 0.5 for the Russian ruble and Turkish lira, while reclassifying Brazil and South Africa as break-driven rather than long-memory currencies—a corrective finding relative to prior work. Across four geopolitical shock events, emerging-market currencies exhibit 2.7 to 12.1 times larger abnormal volatility than developed-market currencies, with the disparity systematically larger in countries scoring below median on all three institutional dimensions. The GARCH-MIDAS-X model reduces out-of-sample RMSE by 25–40% over 2019–2023, confirmed by Diebold-Mariano tests.**

***Index Terms*—Geopolitical risk; GARCH-MIDAS; local projections; HAR-RV; institutional transmission; external instrument; emerging markets; long memory**

JEL Codes: F31, F52, G15, C22, C23

I. INTRODUCTION

The Russian ruble lost 44% of its value against the US dollar in the three weeks following the invasion of Ukraine in February 2022. Over the same period, the euro—also exposed to the conflict's economic spillovers—depreciated by just 3.8%. The tenfold differential is not explained by purchasing power differentials, uncovered interest parity deviations, or global risk appetite as measured by the VIX: all three channels affect both currencies simultaneously. It reflects something more fundamental: the institutional capacity of each currency's anchoring country to absorb and stabilise external shocks.

The literature has established that geopolitical risk (GPR) predicts exchange rate volatility (Caldara and Iacoviello, 2022; Balli et al., 2022; Phan et al., 2021), that this relationship is stronger for emerging-market (EM) currencies than developed-market (DM) currencies (Chen et al., 2022; Jiang et al., 2020), and that GARCH-type models incorporating GPR improve out-of-sample forecasts (Chevapatrakul, 2019). What the literature has not established is: (i) a formal theoretical mechanism explaining why institutions moderate GPR transmission and generating testable cross-country predictions; (ii) causal identification of the GPR effect beyond Granger-causality tests; (iii) a mixed-frequency estimation framework that correctly maps monthly GPR to daily exchange rate dynamics without the temporal aggregation bias introduced by naive observation repetition; and (iv) a rigorous discrimination of genuine long memory from structural-break-induced spurious persistence in EM currency volatility.

This paper addresses all four gaps. We derive a three-equation model of exchange rate variance under geopolitical uncertainty that generates testable predictions about the role of central bank independence (CBI), foreign-currency debt, and reserve adequacy in moderating GPR transmission. We implement GARCH-MIDAS-X and HAR-RV models as the primary estimation framework and construct a geographic distance- and trade-adjusted external GPR instrument—a Bartik-type measure—to embed within two-stage local projections (2SLS-LP) for causal identification. The 2SLS first-stage F-statistic of 18.4 exceeds the Stock-Yogo (2005) threshold for strong instruments; 2SLS and OLS impulse responses are statistically indistinguishable, providing reassuring evidence against reverse causality for the average currency. We apply the Perron-Qu (2010) test throughout to prevent the well-documented spurious long-memory bias from structural breaks.

Our three contributions to the literature are precise. First, we provide the first theoretically grounded institutional moderation framework for GPR-forex transmission, with model-implied predictions that are directly tested and confirmed: the cross-currency gradient in GPR sensitivity tracks the institutional buffer index ranking with a rank correlation of 0.89. Second, we introduce 2SLS-LP identification with an external GPR instrument to this literature, moving beyond Granger-causality and event-study supplementation toward a design that explicitly addresses the endogeneity of GPR to global economic conditions. Third, we correct the long-memory claims of prior work for Brazilian real and South African rand, showing that their elevated persistence parameters reflect structural regime shifts rather than fractional integration, with different implications for risk-model recalibration.

We are explicit about the boundaries of our findings. The 2SLS instrument addresses the correlation between GPR and global economic conditions but does not provide unconditional structural identification equivalent to a randomised experiment. Our sample of eleven currency pairs was chosen to maximise institutional heterogeneity at the EM and DM extremes and is not representative of the full global currency distribution; results should not be extrapolated to frontier or commodity-currency pairs without additional evidence. Within these boundaries, the evidence for GPR-driven volatility amplification in institutionally fragile currencies is robust, theoretically coherent, and economically material.

II. THEORETICAL FRAMEWORK

2.1 A Three-Equation Model of GPR Transmission

Consider an economy with a floating exchange rate e_t (log units; increase = depreciation). Net capital flows K_t respond to the excess return on domestic assets and to a geopolitical risk premium:

$$K_t = -\varphi \cdot G_t + \alpha \cdot (r_t - r^*_t) + \varepsilon_{K,t}$$

where G_t is the GPR index, $r_t - r^*_t$ is the interest rate differential, $\varphi > 0$ is the geopolitical risk aversion of international investors, and $\varepsilon_{K,t}$ is an orthogonal disturbance. GPR raises the required risk premium on domestic assets, generating capital outflows ($K_t < 0$) that depreciate the exchange rate. A central bank with intervention capacity Ψ_i responds:

$$\Delta e_t = -\eta \cdot K_t - \Psi_i \cdot K_t = -\eta(1 + \Psi_i) \cdot K_t$$

where $\eta > 0$ maps capital flows to exchange rate changes and $\Psi_i \geq 0$ is country-specific intervention capacity. Taking the conditional variance of Δe_t with respect to the GPR shock G_t (treating ε_K as orthogonal):

$$\mathrm{Var}(\Delta e_t \mid G_t) = [\eta(1 + \Psi_i) \cdot \varphi]^2 \cdot \sigma^2_G$$

This yields two testable predictions central to our empirical design. First, for any given σ^2_G, the exchange rate variance response is increasing in φ (investor risk aversion) and decreasing in Ψ_i (intervention capacity). Second, if $\Psi_i = f(CBI_i, Res_i, -FXDebt_i)$ — where CBI is central bank independence, Res is reserve adequacy, and FXDebt is the foreign-currency debt burden — then $\partial \mathrm{Var}/\partial CBI < 0$, $\partial \mathrm{Var}/\partial Res < 0$, and $\partial \mathrm{Var}/\partial FXDebt > 0$. These three signed directional predictions map directly to the institutional interaction terms in the HAR-RV panel specification and provide a disciplined basis for the moderation analysis.

The model also predicts asymmetric responses to GPR escalation versus de-escalation: because Ψ_i is constrained by reserve depletion during escalation phases, the denominator $(1 + \Psi_i)$ shrinks precisely when $\varphi \cdot \sigma^2_G$ is largest, amplifying the nonlinearity. This convexity in the variance-GPR relationship is the theoretical motivation for the EGARCH leverage specification in Tier 3.

2.2 Safe-Haven Currencies

For safe-haven currencies (CHF, JPY, USD), $\varphi < 0$: geopolitical escalation attracts capital inflows rather than triggering outflows, because these currencies serve as the numeraire of global risk-off portfolios (Habib and Stracca, 2012; Menkhoff et al., 2012). The model predicts either attenuated or negative GPR volatility effects for these currencies, consistent with H1.

2.3 Formal Hypotheses

H1: The MIDAS long-run variance slope θ is positive and significant for EM currencies and attenuated or negative for safe-haven (CHF, JPY) currencies.

H2: The GPR × Institutional Buffer interaction is negative in the HAR-RV panel: higher CBI, greater reserve adequacy, and lower FX debt each reduce the marginal GPR effect on realised volatility.

H3: 2SLS-LP impulse responses for EM currencies remain elevated beyond 30 trading days following a GPR shock; genuine long memory ($d > 0.5$, confirmed by Perron-Qu test) holds for RUB and TRY.

H4: GPR escalation generates larger conditional variance increases than equivalent de-escalation generates decreases (EGARCH leverage effect; negative γ_lev).

III. DATA

We study eleven bilateral USD spot exchange rates from January 2004 to December 2023 (5,217 daily observations per pair; 57,387 total). The five DM pairs—EUR, GBP, JPY, CHF, CAD—cover the world's most liquid forex markets. The six EM pairs—CNY, INR, BRL, ZAR, RUB, TRY—were selected to maximise variation along the three institutional dimensions predicted by the model: they span low- and high-CBI countries, low- and high-FX-debt countries, and countries with reserve adequacy both above and below the IMF ARA threshold. This selection is purposive, not random; it provides maximum discriminating power to test the institutional moderation hypothesis at the cost of external validity beyond institutionally extreme currency pairs. We acknowledge explicitly that MXN, KRW, SGD, AUD, and SEK—which may occupy intermediate institutional positions—are excluded.

The geopolitical risk index of Caldara and Iacoviello (2022) is measured monthly and sourced from the Federal Reserve Board. The index's news-based construction is described in detail by its authors; its predictive validity for macroeconomic outcomes is established in the same study. Institutional moderator data are from three sources: CBI scores from Dincer and Eichengreen (2014) updated through 2023; foreign-currency sovereign debt ratios from the BIS debt statistics database; and reserve adequacy from the IMF Assessing Reserve Adequacy (ARA) composite metric. The control variable set includes the VIX (global risk appetite), the Baker et al. (2016) EPU index (policy uncertainty distinct from GPR), the TED spread (interbank liquidity stress), bilateral interest rate differentials, bilateral inflation differentials, and the Brent crude oil price change. Monthly realised volatility is computed as the sum of squared daily log-returns within each calendar month. Appendix Table A10 provides full variable definitions, sources, and transformation details.

Table 1 reports pre-estimation diagnostics. All return series are stationary by ADF ($p < 0.001$). ARCH effects are confirmed for all pairs by the Engle (1982) LM test and Ljung-Box Q(20) on squared returns (all $p < 0.001$), justifying GARCH estimation. Descriptive statistics appear in Table 2. The monotonic increase in annualised volatility from CHF (8.2%) to TRY (28.1%) and in the GPR-realised volatility correlation from CHF (0.18) to RUB (0.61) is consistent with the institutional buffer gradient predicted by the theoretical model.

Table 1 Pre-Estimation Diagnostics

Currency	Market	ADF t-stat	ARCH LM F	Ljung-Box Q(20)
CHF	DM	−44.2***	34.2***	389.4***
EUR	DM	−47.1***	52.8***	421.6***
JPY	DM	−46.8***	48.6***	408.2***
GBP	DM	−43.9***	67.3***	474.1***
CAD	DM	−45.3***	73.4***	512.8***
CNY	EM	−42.6***	88.1***	634.3***

INR	EM	−44.8***	112.4***	712.6***
BRL	EM	−43.1***	134.7***	824.5***
ZAR	EM	−41.7***	142.8***	891.2***
RUB	EM	−38.4***	168.3***	1,024.7***
TRY	EM	−36.9***	187.6***	1,189.3***

Note. ADF = Augmented Dickey-Fuller (constant and trend; SIC lag selection). Critical value (1%): −3.43. ARCH LM = Engle (1982) F-test (10 lags). Ljung-Box Q(20) on squared returns. *** $p < 0.001$.

Table 2 Descriptive Statistics: Daily Log-Returns and Monthly Realised Volatility, 2004–2023

Curr.	Mkt.	Mean (%)	SD (%)	Ann. Vol.	Skew.	Exc. Kurt.	JB (p)	GPR–RV ρ
CHF	DM	0.002	0.52	8.20%	0.31	2.8	<.001	0.18
EUR	DM	0.001	0.58	9.20%	−0.12	3.3	<.001	0.22
JPY	DM	−0.001	0.61	9.70%	0.18	2.9	<.001	0.19
GBP	DM	0	0.67	10.60%	−0.24	4.1	<.001	0.24
CAD	DM	0.001	0.71	11.20%	−0.15	2.2	<.001	0.28
CNY	EM	−0.001	0.7	11.00%	0.09	2.5	<.001	0.21
INR	EM	−0.002	0.89	14.10%	−0.42	5.3	<.001	0.37
BRL	EM	−0.003	1.14	18.00%	−0.67	7.2	<.001	0.44
ZAR	EM	−0.002	1.21	19.10%	−0.51	8.8	<.001	0.48
RUB	EM	−0.004	1.4	22.10%	−1.21	13.4	<.001	0.61
TRY	EM	−0.008	1.78	28.10%	−1.82	19.4	<.001	0.54

Note. Ann. Vol. = daily SD × √252. Exc. Kurt. = excess kurtosis. JB = Jarque-Bera p-value. GPR–RV ρ = Pearson correlation between monthly GPR and monthly realised volatility. USD excluded as numeraire. Source: Authors' calculations, Refinitiv Eikon, OANDA.

IV. ECONOMETRIC STRATEGY

Our strategy uses four models, each motivated by a specific gap in the prior literature, organised in two tiers. Tier 1 provides primary estimation: GARCH-MIDAS-X for currency-level conditional variance (H1, H4) and HAR-RV panel fixed effects for cross-country moderation (H2). Tier 2 provides identification and persistence analysis: 2SLS local projections with an external GPR instrument (H1, H3) and ARFIMA/Perron-Qu for long-memory discrimination (H3). All secondary analyses—EGARCH leverage, quantile regressions, VaR backtests, Parkinson volatility, alternative GPR sub-indices—are reported in the Online Appendix as supporting evidence rather than primary results.

4.1 GARCH-MIDAS-X (Tier 1, Primary Volatility Model)

The GARCH-MIDAS model of Engle et al. (2013) decomposes conditional variance σ^2_t into a short-run daily GARCH component g_t and a long-run monthly component τ_i driven by GPR:

$$\sigma^2_t = g_t \times \tau_i$$

$$g_t = (1 - \alpha - \beta) + \alpha(\varepsilon_{t-1} / \sqrt{\tau_{i-1}})^2 + \beta \cdot g_{t-1}$$

$$\log(\tau_i) = m + \theta \cdot \Sigma_{k=1}^{K} \varphi_k(\omega_1,\omega_2) \cdot GPR_{i-k}$$

where $\varphi_k(\omega_1, \omega_2)$ are beta polynomial weighting functions distributing K = 12 lagged monthly GPR observations across the long-run variance component. θ is the MIDAS slope: the primary coefficient of interest for H1. The MIDAS framework avoids the two central methodological weaknesses of prior GARCH-X work: (i) it does not repeat a single monthly GPR value across 20 daily observations, eliminating artificial serial correlation in the variance equation; (ii) the multiplicative $\tau_i \times g_t$ decomposition absorbs permanent variance level shifts into τ_i, resolving the near-integrated GARCH persistence for RUB and TRY. Student-t error distribution; QML with Bollerslev-Wooldridge robust standard errors. Model selection across K = {6, 12, 24} and polynomial degrees {1, 2} uses AIC; results in Appendix Table A1.

4.2 HAR-RV Panel Fixed Effects (Tier 1, Primary Cross-Country Model)

Using monthly realised volatility RV_it (sum of squared daily log-returns) as the directly observable dependent variable eliminates the generated-regressor bias from using GARCH-estimated σ^2_t in a second-stage regression. The HAR-RV specification (Corsi, 2009) augmented with GPR, controls, and continuous institutional interaction terms is:

$$RV_{it} = c_i + \beta_D RV_{it-1} + \beta_W RV_{it-1}{}^W + \beta_M RV_{it-1}{}^M + \gamma \cdot GPR_t + \Sigma_k \beta_k \Gamma_{kit} + \Sigma_j \delta_j (GPR_t \times Z_{jit}) + \varepsilon_{it}$$

where c_i are country fixed effects; Γ_kit are macroeconomic controls (VIX, EPU, TED spread, interest rate differential, inflation differential, oil price change); and Z_jit are the three continuous institutional moderator variables: CBI score (Dincer-Eichengreen), FX-debt ratio (BIS), and reserve adequacy (IMF ARA). The interaction terms GPR × Z_jit test H2: the signed prediction from the theoretical model is δ_{CBI} < 0, δ_{ARA} < 0, and δ_{FXDebt} > 0. Driscoll-Kraay (1998) standard errors correct for cross-sectional dependence and heteroskedasticity. Year fixed effects absorb common time trends.

4.3 2SLS Local Projections (Tier 2, Identification Model)

Local projections (Jordà, 2005) estimate non-parametric impulse response functions for the effect of GPR shocks on realised volatility. To address the endogeneity of the GPR index to global economic conditions—a concern that Granger causality and unconditional event studies cannot resolve—we instrument for the monthly GPR innovation using a geographic distance- and trade-adjusted external GPR measure.

The instrument ExtGPR_i,t is constructed as a weighted average of GPR shocks in countries that are geographically distant from country i and have bilateral trade shares below 2% of country i's total trade:

$$ExtGPR_{i,t} = \Sigma_{j\neq i}\ \omega_{ij} \cdot \Delta GPR_{j,t}$$

where ω_ij = (1/dist_ij) × 𝟙(trade_ij < 0.02), with dist_ij the great-circle distance in thousands of kilometres. The exclusion restriction requires that external GPR shocks in distant, trade-unlinked countries affect country i's forex volatility only through the global GPR channel—not through direct trade, investment, or commodity price linkages. This is a Bartik-type shift-share instrument analogous to those used in international trade and migration literatures (Goldsmith-Pinkham et al., 2020). For example, ExtGPR for the Indian rupee uses GPR shocks driven by events in South America and sub-Saharan Africa, regions with minimal bilateral trade linkages to India but subject to the same global news-aggregated GPR index. The instrument is therefore valid insofar as third-country conflicts influence the global GPR index but do not directly affect Indian macroeconomic conditions. The main threat to validity would be global commodity price shocks that simultaneously affect GPR and EM currencies; the inclusion of oil price changes and the TED spread in the LP control set partially addresses this.

The 2SLS-LP system is:

First stage: $$\Delta GPR\_t = \mu + \delta \cdot ExtGPR_{i,t} + \Sigma_j \lambda_j X_{t-j} + v_t$$

Second stage: $$\Delta RV_{i,t+h} = \alpha_i{}^h + \beta^h \cdot \Delta G\hat{P}R_t + \Sigma \gamma_j{}^h \cdot X_{i,t-j} + \varepsilon_{i,t+h}$$

where $\Delta G\hat{P}R$_t is the first-stage fitted value and h = 0, 1, ..., 60 trading days. The sequence {β^h} traces the causal impulse response of realised volatility to an externally driven GPR shock, conditional on the included controls. Newey-West (1987) standard errors correct for the moving-average disturbance in LP residuals; panel-corrected inference uses country fixed effects.

4.4 ARFIMA and Perron-Qu (Tier 2, Long-Memory Discrimination)

Fractional differencing parameters d are estimated by the exact local Whittle method of Shimotsu and Phillips (2005) with bandwidth m = T^0.65. Because structural breaks create spurious long-memory estimates—a bias documented by Granger and Hyung (2004) and formally tested by Perron and Qu (2010)—we apply the Perron-Qu test to every currency's realised volatility series. The null hypothesis is genuine long memory; rejection implies that apparent persistence is attributable to level shifts rather than fractional integration, with substantively different implications for risk management.

V. RESULTS

5.1 GARCH-MIDAS-X Estimates (H1 and H4)

Table 3 reports GARCH-MIDAS-X estimates. The MIDAS slope θ is positive and significant at the 5% level or better for nine of eleven pairs. CHF ($\theta = 0.011$, $p = 0.138$) and JPY ($\theta = 0.014$, $p = 0.072$) are attenuated, consistent with safe-haven inflow dynamics. Short-run GARCH persistence ($\alpha + \beta$ of the g_t component) averages 0.889 for DM and 0.908 for EM currencies—materially lower than the near-IGARCH values reported by GARCH-X studies, because the MIDAS τ_i component now absorbs the structural variance level shifts that previously inflated GARCH persistence. This confirms that prior claims of near-unit-root GARCH persistence in RUB and TRY were partially an artefact of the frequency mismatch, not a fundamental feature of those series.

The economic magnitude of θ is interpreted as follows. A one-standard-deviation increase in GPR (+31 index points, the mean crisis-period monthly change) raises TRY's long-run variance component τ_i by 8.9% and EUR's by 2.0%—a ratio of 4.5, closely matching the panel interaction estimate in Section 5.2 and consistent with the model's prediction that variance response scales with institutional buffer. EGARCH leverage parameters (Appendix Table A5) are negative for all eleven pairs, confirming H4: adverse GPR shocks amplify conditional variance more than positive shocks reduce it, with asymmetry magnitude increasing from DM (mean $\gamma_{lev} = -0.079$) to EM (mean $\gamma_{lev} = -0.144$).

Out-of-sample evaluation over 2019–2023 shows RMSE reductions of 25–40% relative to GARCH-MIDAS without GPR; Diebold-Mariano tests confirm significance for nine of eleven pairs. To address the concern that COVID-19 mechanically inflates these gains, we report separate test windows for 2019-only (pre-COVID: RMSE reductions 14–21%) and 2021–2023 (post-COVID conflict: 28–44%); GPR forecast gains are present and significant in both sub-periods, confirming they are not pandemic artefacts.

Table 3 GARCH-MIDAS-X Estimation Results and Out-of-Sample Forecast Accuracy

Curr.	Mkt.	α	β	α + β (short-run)	θ (MIDAS slope)	p-value	RMSE Reduction
CHF	DM	0.069	0.818	0.887	0.011	0.138	—
EUR	DM	0.068	0.821	0.889	0.018**	0.028	25%**
JPY	DM	0.072	0.824	0.896	0.014†	0.072	—
GBP	DM	0.065	0.816	0.881	0.022**	0.016	27%**
CAD	DM	0.071	0.82	0.891	0.028**	0.014	28%**
CNY	EM	0.082	0.836	0.918	0.045**	0.021	30%**
INR	EM	0.086	0.841	0.927	0.057**	0.009	33%**
BRL	EM	0.088	0.845	0.933	0.068***	0.003	36%**
ZAR	EM	0.089	0.847	0.936	0.078***	<.001	37%**
RUB	EM	0.091	0.8	0.891	0.092***	<.001	39%**
TRY	EM	0.089	0.788	0.877	0.106***	<.001	40%**

Note. GARCH-MIDAS-X estimated by QML; Student-t errors; Bollerslev-Wooldridge robust SEs. $\alpha + \beta$ = short-run GARCH persistence. θ = MIDAS long-run variance slope on GPR (K = 12 monthly lags, beta polynomial). RMSE Reduction = percentage reduction vs. GARCH-MIDAS without GPR over 2019–2023; Diebold-Mariano test with Harvey et al. (1997) finite-sample correction; '—' not significant at 5%. ***, **, † = 1%, 5%, 10%.

5.2 HAR-RV Panel Fixed-Effects: Institutional Moderation (H2)

Table 4 reports HAR-RV estimates. HAR autoregressive terms are all positive and significant, reproducing the heterogeneous persistence structure of Corsi (2009). The main GPR coefficient $\gamma = 0.016$ ($p = 0.014$) is significant after controlling for VIX, EPU, and TED spread—confirming that GPR retains incremental predictive power beyond these alternative uncertainty channels. The Hausman test rejects random effects ($p = 0.008$), and cross-sectional dependence test (Pesaran, 2021) confirms that Driscoll-Kraay standard errors are appropriate.

The three institutional interaction terms (Panel B) confirm all three signed predictions from the theoretical model. GPR × CBI = −0.034 ($p < 0.001$): higher central bank independence attenuates GPR transmission, consistent with $\partial Var/\partial CBI < 0$. GPR × ARA Reserve = −0.026 ($p = 0.002$): greater reserve adequacy attenuates transmission, consistent with $\partial Var/\partial Res < 0$. GPR × FX Debt = +0.029 ($p < 0.001$): higher foreign-currency debt amplifies transmission, consistent with $\partial Var/\partial FXDebt > 0$. The rank ordering of implied currency-level GPR sensitivity—highest for TRY and RUB (lowest institutional buffer) and lowest for CHF and JPY (highest buffer including safe-haven premium)—reproduces the GARCH-MIDAS θ gradient with a Spearman rank correlation of 0.89, providing cross-model consistency that strengthens the moderation interpretation.

Critically, all three institutional interactions survive exclusion of RUB and TRY from the sample (N reduces from 11 to 9 currencies; Appendix Table A6), confirming that the moderation result is not driven by these two extreme cases. The GPR × CBI interaction remains significant at 5% ($p = 0.021$) and GPR × FX Debt at 1% ($p = 0.006$) in the restricted sample; GPR × ARA becomes marginal ($p = 0.063$) but retains the predicted sign.

Table 4 HAR-RV Panel Fixed-Effects: GPR Level Effect and Institutional Moderation

Variable	Coefficient	SE (Driscoll-Kraay)	p-value
Panel A — Baseline with controls			
RV^D (one-day lag)	0.312***	0.041	<.001
RV^W (one-week lag)	0.218***	0.038	<.001
RV^M (one-month lag)	0.184***	0.033	<.001
GPR (γ)	0.016**	0.007	0.014
GPR × Emerging	0.054***	0.012	<.001
VIX	0.039***	0.009	<.001
EPU (Baker et al., 2016)	0.011**	0.005	0.028
TED Spread	0.014**	0.006	0.019
Interest Rate Differential	0.021**	0.01	0.036
Oil Price Change (%)	0.009*	0.005	0.071
R² within / N observations	0.394 / 57,387	N = 11	Hausman p = 0.008
Panel B — Continuous institutional moderators (GPR × Z interactions)			
GPR × CBI Score	−0.034***	0.009	<.001
GPR × FX Debt Ratio (BIS)	0.029***	0.008	<.001
GPR × Reserve Adequacy (ARA)	−0.026***	0.009	0.002
Robustness: coefficients excl. RUB and TRY (N = 9)			
GPR × CBI Score	−0.027**	0.012	0.021
GPR × FX Debt Ratio	0.024***	0.009	0.006
GPR × Reserve Adequacy	−0.018†	0.01	0.063

Note. Dependent variable: monthly realised volatility RV_it. HAR-RV specification (Corsi, 2009). Driscoll-Kraay (1998) SEs. Country and year FE included throughout. Panel B: continuous institutional moderators (CBI = Dincer-Eichengreen score; FX Debt = BIS FX sovereign debt/GDP; ARA = IMF composite). All results are moderation effects (conditional associations), not mediation pathways. ***, **, *, † = 1%, 5%, 10%, 15%.

5.3 2SLS Local Projections: Causal Identification (H1, H3)

Table 5 reports the 2SLS-LP instrument validity tests and impulse response summaries. The first-stage regression of ΔGPR on ExtGPR produces an F-statistic of 18.4 ($p < 0.001$), exceeding the Stock and Yogo (2005) 5%-bias threshold of 16.38 for one instrument and one endogenous variable, confirming instrument strength. The Hausman-Wu test does not reject exogeneity of ΔGPR for DM currencies ($p = 0.34$–0.58) but is borderline for RUB ($p = 0.09$) and TRY ($p = 0.11$), providing the first evidence in this literature that GPR endogeneity is a more pressing concern for extreme institutional outliers than for the average currency pair.

The 2SLS-LP impulse responses for DM currencies are statistically indistinguishable from OLS-LP responses (Hausman-Wu $p > 0.30$ for all DM pairs), confirming that the Granger-causality and GARCH-MIDAS estimates for DM currencies are not materially biased by reverse causality. For EM currencies, 2SLS impulse responses are 15–25% smaller in the contemporaneous period ($h = 0$) than OLS responses, suggesting a modest upward bias in OLS estimates attributable to the correlation between domestic economic stress and global GPR—but the qualitative pattern (larger EM than DM responses, persistent EM responses beyond 30 days) is preserved. The 2SLS impulse responses for RUB and TRY remain significantly positive through day 42 and day 38 respectively, while DM responses decay to statistical insignificance by day 9–12, confirming H3.

Table 5 2SLS Local Projections: Instrument Validity and Impulse Response Summary

Curr.	Mkt.	1st-Stage F	Wu-Hausman p	LP β^0 (OLS)	LP β^0 (2SLS)	Days Significant (2SLS)
CHF	DM	18.4***	0.52	−0.004	−0.006	Not sig. (safe haven)
EUR	DM	18.4***	0.46	0.012**	0.011**	Days 0–9
JPY	DM	18.4***	0.58	0.008†	0.007†	Days 0–6
GBP	DM	18.4***	0.41	0.014**	0.013**	Days 0–10
CAD	DM	18.4***	0.34	0.016**	0.014**	Days 0–12
CNY	EM	18.4***	0.28	0.031**	0.026**	Days 0–15
INR	EM	18.4***	0.19	0.044**	0.037**	Days 0–22
BRL	EM	18.4***	0.14	0.058***	0.048***	Days 0–24
ZAR	EM	18.4***	0.16	0.063***	0.051***	Days 0–26
RUB	EM	18.4***	0.09†	0.088***	0.071***	Days 0–42
TRY	EM	18.4***	0.11	0.097**	0.079***	Days 0-38

Note. First-stage F = Kleibergen-Paap F-statistic for instrument strength (same instrument across currency pairs; panel first stage). Stock-Yogo 5%-bias threshold: 16.38. Wu-Hausman p = p-value for null of GPR exogeneity; small values indicate endogeneity concern. LP β^0 = contemporaneous impulse response (h = 0) with Newey-West SEs. 'Days Significant' = last horizon h at which 2SLS β^h is significant at 10%. ***, **, † = 1%, 5%, 10%.

5.4 Long Memory and Structural Break Discrimination (H3)

Table 6 reports ARFIMA estimates alongside Perron-Qu (2010) test results. For all five DM currencies, $d < 0.30$ and the Perron-Qu test does not reject genuine short memory ($p > 0.40$). For RUB and TRY, $d = 0.54$ and 0.52 respectively; the Perron-Qu test fails to reject genuine long memory ($p = 0.31$ and $p = 0.27$), confirming fractional integration beyond what structural breaks can explain. Bai-Perron tests identify two to three break dates per EM series (all clustering around 2008, 2014–2015, and 2022), but including estimated break-point dummies as controls does not materially reduce d for RUB or TRY, reinforcing the genuine long-memory classification.

For BRL ($d = 0.47$) and ZAR ($d = 0.46$), the Perron-Qu test rejects genuine long memory ($p = 0.04$ and $p = 0.06$ respectively), attributing their elevated persistence to structural regime shifts rather than fractional integration. This reclassification is a material correction to prior work (Baek and Lee, 2020; Dimitriou et al., 2017), which reported d estimates in the 0.40–0.55 range for these currencies without applying the Perron-Qu discrimination. The implication for risk management is substantive: while VaR recalibration is warranted for RUB and TRY following major geopolitical events (hyperbolic shock decay), for BRL and ZAR the elevated post-event persistence is attributable to discrete regime shifts that can be modelled with Bai-Perron break-adjusted GARCH rather than ARFIMA.

Table 6 ARFIMA Fractional Differencing Parameters and Perron-Qu Discrimination Test

Curr.	Mkt.	d (Full)	d (Pre)	d (Post)	95% CI	Perron-Qu p	Classification
CHF	DM	0.18	0.16	0.22	[0.09, 0.27]	0.64	Short memory
EUR	DM	0.21	0.19	0.28	[0.12, 0.30]	0.58	Short memory
JPY	DM	0.16	0.14	0.21	[0.07, 0.25]	0.71	Short memory
GBP	DM	0.23	0.21	0.29	[0.13, 0.33]	0.52	Short memory
CAD	DM	0.28	0.25	0.34	[0.18, 0.38]	0.47	Short memory
CNY	EM	0.41	0.38	0.48	[0.30, 0.52]	0.18	Borderline
INR	EM	0.44	0.4	0.52	[0.33, 0.55]	0.09	Borderline
BRL	EM	0.47	0.43	0.55	[0.36, 0.58]	0.04*	Break-induced ✗
ZAR	EM	0.46	0.42	0.54	[0.35, 0.57]	0.06†	Break-induced ✗
RUB	EM	0.54	0.42	0.63	[0.43, 0.65]	0.31	Genuine LM ✓
TRY	EM	0.52	0.48	0.59	[0.41, 0.63]	0.27	Genuine LM ✓

Note. d = exact local Whittle, bandwidth m = T^0.65 (Shimotsu and Phillips, 2005). Pre/Post: 6-month windows around Zivot-Andrews break dates. Perron-Qu p = p-value for null of genuine long memory; * and † indicate rejection at 5% and 10% (break-induced spurious persistence). ✓ = confirmed genuine long memory. ✗ = reclassified as break-induced.

5.5 Event Study: Four Geopolitical Shocks (H1, H2)

Table 7 reports abnormal realised volatility from four clean geopolitical events. We exclude the COVID-19 pandemic declaration—which prior reviewers correctly identified as a confounded event mixing health, economic, and geopolitical signals—retaining four episodes with clear geopolitical triggers: the Crimea annexation (March 2014), the US-Iran Soleimani strike (January 2020), the Ukraine invasion (February 2022), and the Israel-Gaza escalation (October 2023). EM currencies exhibit significantly larger abnormal volatility than DM currencies in all four events (Kolmogorov-Smirnov tests: $p < 0.05$ for three of four events; the 2020 US-Iran event yields $p = 0.04$). The GPR spike magnitude monotonically predicts the DM/EM abnormal volatility differential across events, consistent with the model prediction that variance response scales with σ^2_G.

Table 7 Event Study: Abnormal Realised Volatility Around Four Geopolitical Shocks

Event (date; GPR spike in pts)	DM abn. RV [+1,+5]	EM abn. RV [+1,+5]	KS test p	RUB/TRY abn. RV
Crimea annexation (Mar 2014; +42 pts)	+32%**	+127%***	0.023	+389%***
US-Iran: Soleimani strike (Jan 2020; +38 pts)	+28%**	+109%***	0.041	+168%***
Russia-Ukraine invasion (Feb 2022; +91 pts)	+68%***	+241%***	0.004	+814%***
Israel-Gaza escalation (Oct 2023; +47 pts)	+19%*	+68%**	0.038	+88%**

Note. Abnormal RV = % deviation from 120-day rolling pre-event baseline. KS = Kolmogorov-Smirnov two-sample distributional test (H_0: DM and EM distributions equal). RUB/TRY = average of Russian ruble and Turkish lira. ***, **, * = 1%, 5%, 10% vs. pre-event baseline (paired t-test).

VI. ROBUSTNESS ANALYSIS

Four targeted robustness checks are summarized here; full tables are in the Online Appendix.

Exclusion of RUB and TRY. The two currencies with the most extreme GPR sensitivity are excluded from the panel (N reduces to 9). The GPR main effect, GPR × Emerging interaction, and two of three institutional moderation terms remain statistically significant (Table 4, bottom panel). The long-memory and event-study findings are specific to RUB and TRY as the most institutionally fragile currencies in the sample; we do not claim that long memory is a general EM property.

Alternative volatility measures. Results using the Parkinson (1980) range-based estimator and, for four pairs, option-implied volatility are quantitatively similar to the HAR-RV baseline (Appendix Table A3). Implied volatility coefficients are larger in magnitude, consistent with GPR primarily elevating forward-looking uncertainty.

Alternative GPR sub-indices. Replacing the aggregate GPR with GPR Threats or GPR Acts, or with the Ahir et al. (2022) World Uncertainty Index, does not materially alter the primary estimates (Appendix Table A2). GPR Acts produces larger θ for EM currencies, consistent with realised-event shocks generating larger immediate variance responses than threat-based GPR.

Quantile heterogeneity. Quantile regressions at the 25th, 50th, 75th, and 95th percentiles of monthly RV show that GPR coefficients are monotonically increasing toward the upper tail (Appendix Table A7). The 95th-percentile GPR coefficient is 2.1 times the median coefficient for EM currencies, confirming that GPR disproportionately amplifies extreme volatility episodes—a finding relevant for stress-testing and CVaR applications.

VII. ECONOMIC IMPLICATIONS

7.1 Value-at-Risk Recalibration

The confirmed genuine long memory of RUB and TRY has a direct and quantifiable implication. A Kupiec (1995) likelihood-ratio VaR backtest over 2019–2023 shows that a standard GARCH (1,1) model breaches the 99% one-day VaR threshold on 1.9% of days for TRY (Kupiec LR $p = 0.031$, indicating statistical miscalibration) and 1.8% for RUB ($p = 0.043$). The GARCH-MIDAS-X model breaches at 1.1% for TRY ($p = 0.488$) and 1.0% for RUB ($p = 0.512$), well-calibrated. For BRL and ZAR—reclassified as break-induced rather than genuinely long-memory—the appropriate recalibration is Bai-Perron break-adjusted GARCH rather than ARFIMA, which achieves a 1.2% breach rate ($p > 0.30$) in the same backtest period (Appendix Table A8).

7.2 Institutional Reform and GPR Transmission

The continuous moderation coefficients in Table 4 imply that a one-standard-deviation improvement in the Dincer-Eichengreen CBI score—roughly the distance between Turkey's 2020 score and Brazil's 2020 score—is associated with a 0.034-unit reduction in the marginal GPR effect on monthly realised volatility, equivalent to a 26% attenuation relative to the baseline EM GPR coefficient. This is a conditional association from a cross-sectional regression, not a causal estimate of the effect of CBI reform on GPR sensitivity. Moving from the sample-median FX debt ratio to the 25th percentile is associated with a 0.029-unit reduction in the marginal GPR effect—the largest single moderator effect in the model. Reserve accumulation to above the ARA threshold is associated with a 0.026-unit reduction. Taken together, the three channels suggest that institutional reform addressing all three dimensions would narrow the EM/DM GPR sensitivity ratio from 4.4 to approximately 2.8—a meaningful reduction, though still substantially above unity.

VIII. DISCUSSION

Our results speak to three strands of the literature. Against the GPR-finance literature (Caldara and Iacoviello, 2022; Baker et al., 2016; Balli et al., 2022; Phan et al., 2021), we provide the first theoretically grounded institutional moderation framework for the GPR-forex channel, with model predictions that are confirmed by three independently estimated coefficients pointing in the predicted directions. The GARCH-MIDAS specification corrects the frequency mismatch in prior work, and the Perron-Qu discrimination corrects the long-memory overstatement; both are substantive improvements, not merely technical refinements.

Against the exchange rate volatility literature (Menkhoff et al., 2012; Ilzetzki et al., 2019; Engel, 2014), our results document a robust non-macroeconomic driver of conditional variance that survives conditioning on carry trade proxies (interest rate differential), inflation fundamentals, and global liquidity stress (TED spread, VIX). The GPR coefficient in the HAR-RV panel retains significance after including EPU, confirming that it captures geopolitical rather than policy uncertainty.

Against the long-memory literature (Baillie, 1996; Baek and Lee, 2020; Andersen et al., 2003), the Perron-Qu reclassification of BRL and ZAR is the most direct empirical contribution: it shows that the long-memory literature has overstated fractional integration prevalence in EM currencies by failing to systematically apply break discrimination tests. The practical implication—different risk-model recalibration strategies for genuinely long-memory currencies (RUB, TRY) versus break-regime currencies (BRL, ZAR)—is actionable for risk managers.

We acknowledge three limitations that future research should address. First, the 2SLS identification using a geographic external GPR instrument addresses endogeneity from the correlation between GPR and global economic conditions but cannot rule out country-specific omitted variables that simultaneously affect GPR media coverage and domestic forex volatility. An ideal design would use exogenous political shocks with no direct economic content; the Romer and Romer (2010) narrative approach applied to geopolitical events is a promising direction. Second, the N = 11 sample precludes high-power statistical inference on the institutional moderation terms; a 40-currency extension would substantially improve precision and generalisability. Third, the monthly frequency of the GPR index and our realised volatility measures prevents analysis of intraday microstructure effects; order flow data around GPR events would illuminate the specific market participants and channels mediating the shock transmission.

IX. CONCLUSION

We ask why geopolitical risk shocks propagate with four to five times greater force to emerging-market currencies than to developed-market currencies, and answer with a theoretical model and four complementary empirical tests. The answer is institutional: countries with lower central bank independence, higher foreign-currency debt, and lower reserve adequacy provide a weaker buffer against the capital-flight and depreciation-amplification channels through which GPR transmits to exchange rate volatility. Three continuous moderation coefficients—all signed as predicted by the model—confirm this mechanism.

Our methodological contributions are equally substantive. GARCH-MIDAS-X resolves the temporal aggregation bias in prior GARCH-X studies of GPR and daily exchange rates; HAR-RV eliminates the generated-regressor problem from two-stage estimation; 2SLS local projections with a geographic external instrument provide the first attempt at causal identification in this literature beyond Granger causality; and the Perron-Qu test corrects the long-memory overstatement for BRL and ZAR—a finding with direct implications for how practitioners recalibrate VaR models following geopolitical events in those currencies.

The results carry direct implications for risk managers, central banks, and regulators. VaR frameworks without GPR conditioning are statistically miscalibrated for TRY and RUB in the 40–100 days following major geopolitical events. The institutional moderation estimates suggest that reform toward greater central bank independence and lower foreign-currency debt exposure is associated with meaningfully lower GPR sensitivity—a finding that may inform the policy priorities of EM central banks operating in geopolitically exposed environments.

Data Availability and Replication

The Caldara-Iacoviello GPR Index is publicly available at https://www.matteoiacoviello.com/gpr.htm.

Exchange rate data are available from Refinitiv Eikon (subscription) and OANDA (https://www.oanda.com). Replication code in Python 3.11 (arch v5.3; statsmodels v0.14; linearmodels v5.0; custom MIDAS and 2SLS-LP modules) and all constructed data series are deposited in the journal's data repository. The authors declare no conflicts of interest.

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