Remittances and Rupee Volatility across Uncertainty and Exchange Rate Regimes: Threshold GARCH-MIDAS Evidence from Pakistan

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Abstract

Remittances are usually described as a steady source of foreign exchange, but their effect on a currency may depend on the policy setting in which they arrive. This study examines that question for Pakistan, using 2,847 daily PKR/USD returns from the State Bank of Pakistan (August 2014 to February 2026), monthly workers' remittances, Pakistan's economic policy uncertainty (EPU) index, and the global geopolitical risk (GPR) index. It proposes a threshold GARCH-MIDAS model in which the effect of remittance growth on long-run variance switches when lagged uncertainty crosses an estimated threshold, and allows for a structural break in May 2022. On average, a one-percentage-point rise in remittance growth raises long-run variance by about 9%. The effect is far from constant. Controlling for the break, it is about 50% larger when EPU is above roughly 64 than below it, and after May 2022 it vanishes altogether. Bootstrap tests reject a constant effect, both with and without the break, while geopolitical risk produces a weaker threshold. The low-uncertainty regime, however, coincides almost exactly with the 2015–2017 near-peg of the rupee, so uncertainty and exchange rate management cannot be cleanly separated. Interaction terms used in earlier work give conflicting signs, and no model forecasts better out of sample.

Keywords: Remittances, Exchange Rate Volatility, Economic Policy Uncertainty, Geopolitical Risk, Threshold GARCH-MIDAS, Pakistan

JEL classifications: C32, C58, F24, F31, G15

1. Introduction

In May 2026, Pakistan received USD 4.25 billion in workers' remittances, a monthly record and more than two and a half times the average month a decade earlier. Over the same decade, the rupee went through almost every kind of exchange rate management short of a currency board. It was held almost fixed from 2015 to 2017, devalued in steps in 2018 and 2019, and then allowed to float under an IMF programme. In 2022, it came under an informal cap on the interbank rate, and when that cap was dropped in January 2023, the currency was abruptly allowed to fall. These shifts leave a clear mark on the data. The daily PKR/USD return sits close to zero for months, then jumps by more than 6% in a single day. Whether remittances steady the rupee or add to its swings is therefore a live question for the State Bank of Pakistan (SBP), for importers who pay in dollars and for the households that depend on money sent from abroad.

Theory gives remittances two routes to the exchange rate. The first runs through spending. Spent at home, remittances raise demand for non-tradables and push up the real exchange rate, the Dutch-disease effect that Amuedo-Dorantes and Pozo (2004) documented and that Alshubiri et al. (2024) find again across 36 developed and developing economies. The second runs through liquidity. Sold for rupees, remittances add dollar liquidity to the interbank market, and if the flow is steady, it smooths the supply of foreign currency. The standard view that remittances are a stable, countercyclical inflow that dampens exchange rate swings rests on this second route. It assumes that remittances are less volatile than other inflows, that they come through formal channels and that the price at which they are sold is set by the market.

None of these assumptions is safe in Pakistan. Barak and Ünlü (2024) find that policy uncertainty reduces recorded remittances in the ten largest recipient countries. In 2022 and 2023, a wide gap between the interbank and open-market rates is widely reported to have pushed part of the inflow into informal hawala channels, so recorded remittances fell just as the country most needed dollars. For long stretches, the SBP has not let the market set the price at all. Where the money comes from matters as well. SBP's country-wise data show that in fiscal year 2019 Saudi Arabia and the United Arab Emirates together sent about USD 9.6 billion of the USD 21.7 billion Pakistan received, roughly 44%. Flows of that kind follow oil revenues and construction cycles in the Gulf, so they can carry external shocks into Pakistan's dollar market rather than insulate it. Direct evidence on remittances and rupee volatility is nonetheless scarce; related work on emerging-market currencies has looked mostly at oil prices and trade (Imane et al., 2023; Lu et al., 2023; Privara et al., 2025), and in Pakistan oil price shocks have been shown to move domestic asset prices, including Islamic equities (Bhatty et al., 2025).

A separate and larger literature establishes that uncertainty raises exchange rate volatility, and the tools used to show it have become more flexible over time. Aftab et al. (2024) find that uncertainty promotes exchange rate volatility in global data. Nonlinear and quantile ARDL models show that emerging-market currencies react asymmetrically to extreme changes in policy uncertainty (Gohar et al., 2022b; Maydybura et al., 2023), and quantile and time-varying methods find that the links among currencies, oil and equities shift with market conditions (Aldawsari et al., 2024; Hashmi et al., 2022; Lu et al., 2023). Uncertainty also spreads beyond currencies to equity, commodity, and carbon markets (Gohar et al., 2023; Jin et al.,

2025; Tu et al., 2024; Uddin et al., 2025). Not every result points the same way. Yilmazkuday (2025) finds that geopolitical shocks depreciate some currencies and appreciate others across 35 countries, so the sign of an uncertainty effect has to be settled empirically.

Mixed-frequency models have become the natural tool for this question because they let monthly uncertainty feed directly into daily volatility. Engle et al. (2013) split volatility into a slow long-run component tied to macroeconomic variables and a fast GARCH component, and Conrad and Kleen (2020) show that this multiplicative structure forecasts better than single-component models. Using this framework, Salisu et al. (2022) show that geopolitical risk forecasts the volatility of BRICS currencies; Salisu et al. (2024) find the same for energy-market uncertainty across 19 exchange rates; Ekeocha et al. (2025) study exchange rate volatility under domestic and global uncertainty, and Wei et al. (2025) report that EPU predicts currency volatility in several economies. Lateef (2026), applying the same framework to Nigeria, reaches a conclusion that runs against the standard view of remittances. Remittances there amplify exchange rate volatility, and the amplification grows when remittances are interacted with economic policy uncertainty (Baker et al., 2016) or geopolitical risk (Caldara & Iacoviello, 2022).

A third strand points towards regimes. On the econometric side, Segnon et al. (2024) add Markov switching to GARCH-MIDAS and find that geopolitical risk predicts stock volatility better once regimes are allowed. On the empirical side, exchange rates and related variables respond asymmetrically to their drivers, and the response changes across market states (Chang et al., 2024a, 2024b; Gohar et al., 2022a; Gong et al., 2023; Hashmi & Chang, 2023; Mei et al., 2024; Peng et al., 2022). In Pakistan, political violence and terrorism add another source of state dependence (Chang et al., 2022).

We are not convinced that an interaction term can answer the question Lateef (2026) poses. A product such as remittances times EPU forces the remittance effect to rise or fall in a straight line with uncertainty. It cannot tell the difference between a case where uncertainty strengthens the remittance channel and one where something else that moves with uncertainty does the work. On Pakistani data, the problem is visible at once: the interaction slope is negative with EPU and positive with GPR. A transmission mechanism should not change sign with the choice of uncertainty index. The economic question is easier to pose with regimes. Is the remittance effect on long-run volatility different when uncertainty is high? Where is the boundary? And is the regime really about uncertainty, or about something that changes at the same time?

Several gaps follow from this review. To begin with, it has not been tested whether the remittance channel switches with uncertainty, as opposed to being scaled by it; Lateef (2026) and the wider uncertainty literature use linear slopes or interaction terms. Second, the same studies treat the exchange rate regime as fixed, so it is unknown whether any switch survives once known changes in exchange rate management are taken into account. Third, evidence for Pakistan is thin, even though it is among the world's largest remittance recipients and offers a country-specific EPU index (Choudhary et al., 2020) that allows domestic policy risk to be kept apart from global geopolitical risk.

It is against this background that the present study examines how remittances affect rupee volatility across uncertainty and exchange rate regimes. The study makes three additions to the literature. First, it proposes

a threshold GARCH-MIDAS model in which the MIDAS slope on remittance growth takes one value below an estimated threshold of lagged uncertainty and another above it, with a separate intercept for each regime and, in the preferred specification, a structural break in May 2022. Linearity is tested with a parametric-bootstrap sup-LR statistic that handles the nuisance-parameter problem of Hansen (1996), and the threshold comes with a likelihood-ratio confidence set. Second, it applies the model to Pakistan, where policy uncertainty has been unusually high since 2022, using official SBP data and separate domestic and global uncertainty measures. Third, it compares all models on expanding-window forecasts, so a better in-sample fit cannot pass as a better model, and it checks whether the estimated regimes reflect uncertainty or the way the rupee was managed. That last check matters most. It shows that remittances matter for currency risk under a managed float and matter much less when the rate is held or administered.

2. Data and Methodology

2.1 Data Description

This paper studies the effect of remittances on PKR/USD volatility using daily exchange rate data and monthly remittance and uncertainty data. For the exchange rate, we use the daily average PKR per USD rate in the bank floating market, published by the SBP on its EasyData portal (series TS_GP_ES_FADERPKR_M.XRDAVG0220). We chose the official series over a vendor quote because vendor feeds for the rupee contain stale prices and occasional bad ticks; Yahoo Finance quotes, for example, are off by more than 5% on several days. Daily returns are computed as

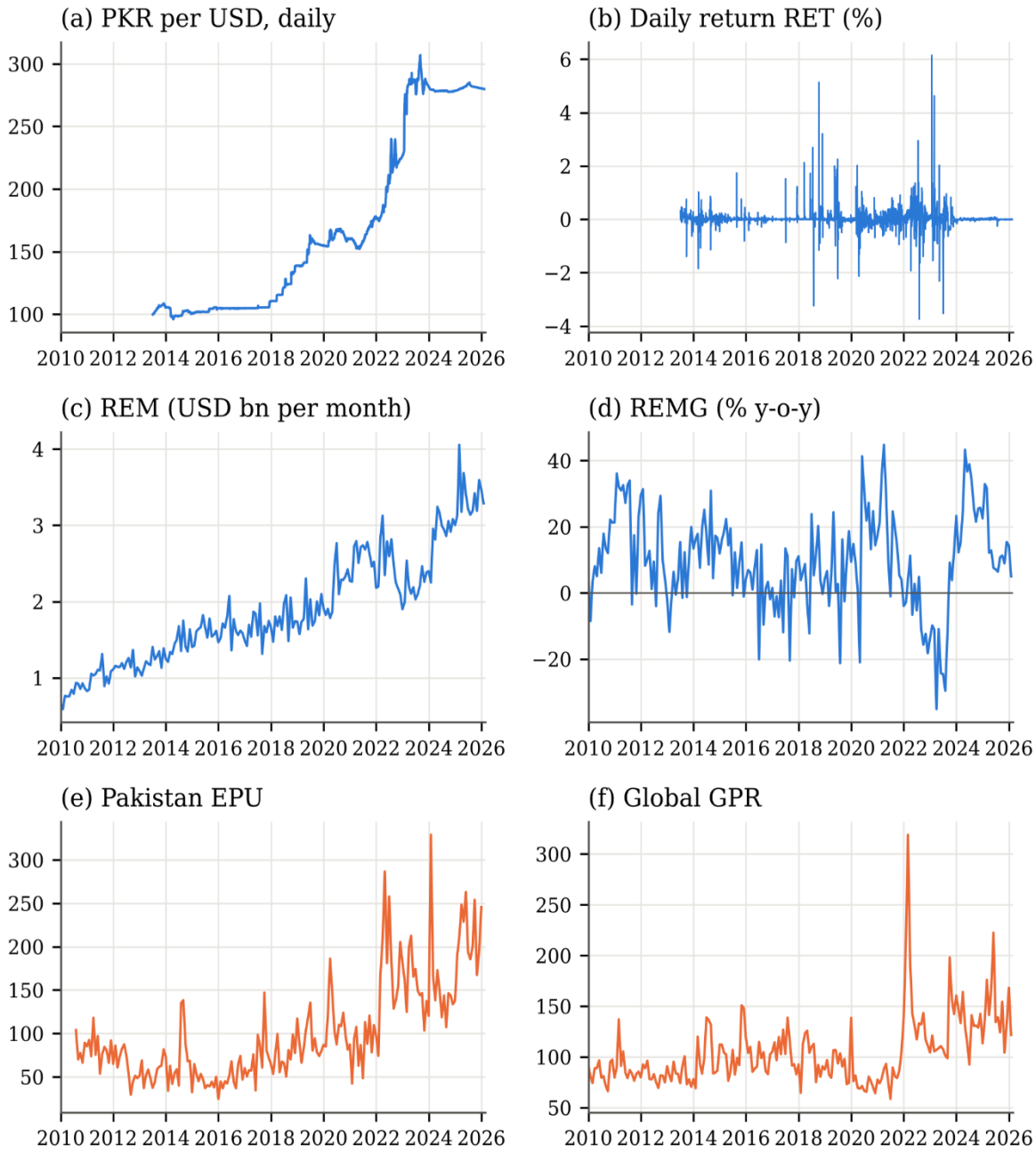
$$r_{i,t} = 100 \times \ln\left(\frac{S_{i,t}}{S_{i-1,t}}\right), \tag{1}$$

where $S_{i,t}$ is the rate on day i of month t, so a positive return means the rupee depreciated.

Remittances (REM) are SBP's total cash inflow of workers' remittances in USD million (series TS_GP_BOP_WR_M.WR0010). Policy uncertainty is measured with the Pakistan EPU index of Choudhary et al. (2020), which follows the newspaper-count method of Baker et al. (2016). The two-newspaper version starts in August 2010 and is our main measure; the four-newspaper version serves as a check. Geopolitical risk is measured with the benchmark global index of Caldara and Iacoviello (2022). All series were downloaded on 11 October 2026.

Two constraints set the sample. The SBP daily series starts in July 2013, and the MIDAS filter needs twelve months of lagged data, so estimation begins on 1 August 2014. The Pakistan EPU index currently ends in January 2026, the last month that can enter the long-run component for February 2026, so estimation ends on 27 February 2026. That gives 2,847 daily returns over 139 months. The window suits the question because it covers the near-peg of 2015 to 2017, the devaluations of 2018 and 2019, COVID-19, the 2022 political crisis, the January 2023 unification of the interbank and open-market rates, and the calm that followed. Figure 1 plots them, and Table 1 defines the variables.

Figure 1. Exchange Rate, Remittances and Uncertainty Indices



Notes: (a) SBP daily PKR/USD rate and (b) daily return (%), July 2013 to February 2026. (c) Monthly remittances (USD bn) and (d) their year-on-year growth (%). (e) Pakistan EPU and (f) global GPR, from January 2010.

Table 1. Definition of Variables and Data Sources

Variable	Definition and construction	Frequency	Source
S(i,t)	PKR per USD, daily average bank-floating (interbank) rate	Daily	SBP EasyData, TS_GP_ES_FADERPKR_M.XRDAVG0220
r(i,t)	Return, 100 × ln(S(i,t)/S(i−1,t)); positive = depreciation	Daily	Derived

REM(t)	Total cash inflow of workers' remittances, USD million	Monthly	SBP EasyData, TS_GP_BOP_WR_M.WR0010
REMG(t)	Year-on-year growth, 100 × (ln REM(t) − ln REM(t−12)), demeaned	Monthly	Derived
EPU(t)	Pakistan economic policy uncertainty index (two-newspaper; four-newspaper for robustness)	Monthly	Choudhary et al. (2020), policyuncertainty.com
GPR(t)	Global geopolitical risk index (benchmark)	Monthly	Caldara and Iacoviello (2022)
RV(t)	Monthly realised variance, Σ_i r(i,t)²	Monthly	Derived
REM×EPU, REM×GPR	Product of standardized REMG(t) and standardized ln EPU(t) or ln GPR(t)	Monthly	Derived
s(t−1)	Regime state: mean of ln U over months t−1 to t−3, U ∈ {EPU, GPR}	Monthly	Derived
B(t)	Break dummy, equal to 1 from May 2022	Monthly	Derived

Notes: SBP = State Bank of Pakistan. All series accessed on 11 October 2026. The daily estimation sample runs from 1 August 2014 to 27 February 2026 (2,847 returns, 139 months). Monthly variables enter the long-run component with lags of 1 to 12 months. No observation is interpolated, deleted or winsorized.

Remittances peak around the two Eid festivals and trend upward, so we use year-on-year log growth, demeaned so that the MIDAS intercept refers to average growth:

$$\mathrm{REMG}_t = 100 \times (\ln \mathrm{REM}_t - \ln \mathrm{REM}_{t-12}). \tag{2}$$

Annual differencing removes the seasonal pattern without a filter that looks ahead. The regime state for month t is the average of the log uncertainty index over months $t-1$ to $t-3$. It is known when the month begins, and averaging over three months keeps a single news spike from flipping the regime. For the interaction benchmarks, we multiply standardized remittance growth by standardized log uncertainty. Lateef (2026) does not report how the interaction is constructed, so this is our closest reading. Every transformation is documented in the dataset workbook, and no observation is interpolated, deleted, or winsorized.

2.2 Econometric Methodology

2.2.1 Preliminary Analysis

Before estimating the models, we examine the distributional properties of the variables: the mean, standard deviation, skewness, kurtosis, and the Jarque-Bera test of normality. Returns on a managed currency are expected to be far from normal, and the shape of the tails decides which likelihood we use. Stationarity is tested with the Augmented Dickey-Fuller (ADF) and KPSS tests. Their null hypotheses run in opposite directions, so a conclusion supported by both is less likely to reflect low test power. Ljung-Box statistics on levels and squares and the ARCH-LM test check for serial dependence and conditional heteroskedasticity, which justify a volatility model in the first place. After estimation, Ljung-Box tests on

standardized residuals and their absolute values confirm whether each model has absorbed that dependence (Table 3, Panel B).

2.2.2 GARCH-MIDAS Model Specification

Engle et al. (2013) write returns as the product of a long-run component $\tau(t)$, fixed within month t, and a short-run component $g_{i,t}$ with unit mean:

$$r_{i,t} = \mu + \sqrt{\tau_t g_{i,t}}\varepsilon_{i,t}, \qquad \varepsilon_{i,t} \sim t_\nu(0,1), \tag{3}$$

where $\varepsilon_{i,t}$ is a standardized Student-t innovation with ν degrees of freedom. The short-run component is a GJR-GARCH(1,1) process (Glosten et al., 1993):

$$g_{i,t} = \left(1 - \alpha - \beta - \frac{\gamma}{2}\right) + \frac{\left(\alpha + \gamma I_{i-1,t}\right)\left(\left(r_{i-1,t} - \mu\right)^2\right)}{\tau_t} + \beta g_{i-1,t}. \tag{4}$$

The indicator $I_{i-1,t}$ equals one after a positive return, so γ captures any extra volatility that follows a depreciation compared with an appreciation of the same size. We impose $\alpha > 0, \beta > 0$ and $\alpha + \beta + \gamma/2 < 1$. The long-run component is modelled in logs, which keeps it positive:

$$\ln \tau_t = m + \theta \sum_{k=1}^{K} \varphi_k(\omega) X_{t-k}\,, \tag{5}$$

where X_{t-k} is the monthly driver lagged k months, $K = 12$, and the weights come from a restricted beta polynomial:

$$\varphi_k(\omega) = \frac{\left(1 - \frac{k}{K+1}\right)^{\omega-1}}{\sum_{j=1}^{K}\left(1 - \frac{j}{K+1}\right)^{\omega-1}}\,. \tag{6}$$

The weights are positive, sum to one and decline with the lag when $\omega > 1$. Only lags $k \geq 1$ enter, so $\tau(t)$ uses information available before month t starts. We estimate four benchmarks. In GM-RV the driver is monthly realised variance, RV(t) = Σ r(i,t)². In GM-REM it is remittance growth, REMG(t). In GM-REM×EPU and GM-REM×GPR it is the corresponding interaction term.

2.2.3 Threshold GARCH-MIDAS Model with a Structural Break

The proposed model keeps Equations (3), (4) and (6) and replaces Equation (5) with

$$\ln \tau_t = m + \delta_H H_t + \delta_B B_t + [\theta_L(1 - H_t) + \theta_H H_t + \theta_B B_t] \sum_{k=1}^{K} \varphi_k(\omega)\mathrm{REMG}_{t-k}\,, \tag{7}$$

$$H_t = I(s_{t-1} > c), \qquad s_{t-1} = \frac{1}{3}\sum_{j=1}^{3} \ln U_{t-j}\,, \tag{8}$$

where U_t is either EPU or GPR and c is the threshold. The coefficients θ_L and θ_H are the remittance slopes in the low- and high-uncertainty regimes, and δ_H moves the level of long-run log variance in the high regime. B_t equals one from May 2022, the month in which the political crisis, the IMF negotiations and the informal cap on the interbank rate began to dominate the market; δ_B and θ_B let both the level and the remittance slope shift after that date. Setting $\delta_B = \theta_B = 0$ gives the threshold model without a break (TGM). Further setting $\theta_L = \theta_H \; and \; \delta_H = 0$ gives back GM-REM.

The intercepts do real work. Without δ_H, any rise in volatility during uncertain months would have nowhere to go except the remittance slope, which is exactly the confusion an interaction term invites. Without the break, a regime defined by uncertainty could simply be dating the 2022 to 2023 crisis. We place the threshold on uncertainty rather than on remittances because the question is whether the environment changes how remittances matter. The MIDAS weighting parameter ω is common to both regimes; with 139 months, the data cannot pin down two separate lag profiles reliably, and we check this choice in the robustness analysis.

All parameters are estimated by Student-t quasi-maximum likelihood, maximizing

$$\mathcal{L} = \sum_t \sum_i \left[\ln f_\nu \left(\frac{r_{i,t} - \mu}{\sqrt{\tau_t g_{i,t}}} \right) - \frac{1}{2} \ln\left(\tau_t g_{i,t}\right) \right], \tag{9}$$

where f_ν is the standardized Student-t density. We evaluate Equation (9) for each threshold on a grid from the 15th to the 85th percentile of s_{t-1}, in steps of five percentiles, and keep the one with the highest likelihood. Standard errors use the robust sandwich form of Bollerslev and Wooldridge (1992), conditional on the estimated threshold.

Because c is unidentified under the null of no regime effect, the likelihood-ratio statistic does not have its usual distribution (Hansen, 1996). We therefore use

$$\mathrm{LR}^* = 2\left[\max_c \mathcal{L}_T(c) - \mathcal{L}_0\right], \tag{10}$$

where $\mathcal{L}_0$ is the log-likelihood of the null model. For TGM, the null is GM-REM. For the threshold model with a break (TGM-B), the null is the break-only model (GM-REM-B), which is Equation (7) with $\delta_H = 0$ and $\theta_L = \theta_H$. The p-value comes from a parametric bootstrap. We simulate return paths from the fitted null model with its Student-t innovations, re-estimate the null and the threshold model on each path, and count how often the simulated LR^* exceeds the observed one. We use 299 replications for EPU and 100 for GPR in the TGM-B tests, and 99 for the TGM tests. To keep the computation manageable, the bootstrap grid moves in steps of ten percentiles; the observed maxima fall on this coarser grid.

Following Hansen (2000), a 95% confidence set for c collects the grid points that satisfy

$$2[\mathcal{L}(\hat{c}) - \mathcal{L}(c)] \leq 7.35. \tag{11}$$

The variance ratio measures how much of the variation in conditional variance the long-run component accounts for:

$$\text{VR} = \frac{\text{Var}(\ln \tau_t)}{\text{Var}\left(\ln\left(\tau_t g_{i,t}\right)\right)}. \tag{12}$$

A Markov-switching GARCH-MIDAS (Segnon et al., 2024) is the obvious alternative. We prefer an observed threshold for two reasons. It gives a policy reading, namely the level of measured uncertainty at which the remittance channel changes, and a lagged state can be used for forecasting without filtering latent regime probabilities.

2.2.4 Model Validation, Robustness and Forecast Evaluation

The threshold models are re-estimated with a 24-month MIDAS window, with the four-newspaper EPU index, with a detrended EPU state, on a sample ending in December 2022, with regime-specific MIDAS weights and under Gaussian QMLE. We also compare TGM-B with a calendar model in which the regime is the 2015 to 2017 near-peg (January 2015 to November 2017) instead of an uncertainty threshold. Model fit is compared with AIC and BIC.

Out-of-sample performance is the stricter test. Each model without a break is re-estimated every six months on an expanding window from January 2022 and forecasts the sum of variance over the next 10, 20 and 30 trading days. Models with the May 2022 break cannot be compared fairly out of sample, because the break date was chosen with hindsight. Forecasts are scored with QLIKE (Patton, 2011) and mean squared error, and compared with the Diebold and Mariano (1995) test using the small-sample correction of Harvey et al. (1997).

2.3 Expected Relationship

Following Lateef (2026), remittance growth is expected to be positively associated with long-run PKR/USD volatility (H1). If the conversion of remittances into rupees depends on the policy environment, the size of that effect should differ between low- and high-policy-uncertainty regimes (H2). Geopolitical risk reaches Pakistan mainly through oil prices and Gulf labor markets, so a similar but weaker regime effect is expected when the state variable is GPR (H3). Finally, if the regime effect reflects something more than the 2022 to 2023 crisis, the regime dependence in H2 and H3 should survive a structural break in May 2022 (H4).

3. Results and Discussion

Table 2 describes a currency that spent long periods doing almost nothing and then moved violently. Daily returns are heavily skewed towards depreciation, and their tails are far fatter than a normal distribution would allow. A managed exchange rate produces exactly this pattern. While the SBP holds the rate, pressure builds up out of sight instead of being released a little each day. When the policy gives way, the adjustment arrives in a few large steps. Remittances were large and rising over the sample, yet their growth swung widely from one year to the next, so the inflow was not the steady stream the stabilization view assumes. Domestic and global uncertainty also followed different paths. Pakistan's policy uncertainty climbed several-fold from its 2016 lows to its 2025 highs, while global geopolitical risk peaked with the invasion of Ukraine in early 2022. That difference is useful, because it lets us ask whether the remittance channel responds to risk made at home or abroad.

Table 2. Descriptive Statistics

Variable	N	Mean	SD	Min	Max	Skewness	Excess kurtosis	Jarque-Bera
r(i,t) (%)	2847	0.037	0.387	−3.75	6.15	3.96	69.27	576,551***
REM(t) (USD mn)	138	2,180.52	610.67	1,314.10	4,053.58	0.72	−0.35	12.5***
REMG(t) (%)	138	8.07	15.18	−35.15	44.75	−0.16	0.18	0.7
EPU(t)	138	111.73	61.40	24.43	328.86	0.97	0.60	23.9***
GPR(t)	138	111.09	35.52	58.42	318.95	2.05	8.01	464.7***

Notes: Daily returns cover 1 August 2014 to 27 February 2026 (2,847 observations); monthly variables cover August 2014 to January 2026 (138 months). Jarque-Bera tests the null of normality. *** $p < 0.01$.

The diagnostics in Panel A of Table 3 justify the modelling choices. The exchange rate and remittances are non-stationary in levels, so the analysis works with returns and remittance growth. Squared returns are strongly autocorrelated: turbulent days follow turbulent days, and calm follows calm. A volatility model is the natural tool. The tails also decide how the model should be estimated. A normal likelihood treats the devaluation days as almost impossible events and lets a handful of them dominate the estimates, whereas a Student-t likelihood expects occasional large moves and fits the data far better. Policy uncertainty is itself non-stationary over this window, which raises a warning that we return to below. A threshold on its level may end up separating periods of history rather than states of uncertainty.

Table 3. Unit Root, Autocorrelation and ARCH Diagnostics

Panel A. Pre-estimation diagnostics of the series					
Series	**ADF**	**KPSS**	**Q(10)**	**Q^2(10)**	**ARCH-LM(10)**
r(i,t)	−10.43***	0.174	875.6***	440.7***	435.4***
ln S(i,t)	−0.08	8.712**	28,316.4***	28,232.8***	2,835.8***
ln REM(t)	−0.28	1.830**	793.9***	280.9***	75.8***
REMG(t)	−2.89**	0.115	236.2***	62.6***	38.3***

ln EPU(t)	−1.18	1.687**	631.9***	103.5***	34.8***
ln GPR(t)	−3.72***	0.685**	240.6***	33.6***	28.8***

Panel B. Post-estimation diagnostics of standardized residuals		
Standardized residuals	**Q(10) on z**	**Q(10) on abs. z**
GM-RV	1.64 [1.00]	2.10 [1.00]
GM-REM	1.12 [1.00]	1.32 [1.00]
GM-REM×EPU	1.11 [1.00]	1.53 [1.00]
GM-REM×GPR	1.12 [1.00]	1.45 [1.00]
TGM-EPU	1.41 [1.00]	1.22 [1.00]
TGM-GPR	1.48 [1.00]	1.40 [1.00]
GM-REM-B	1.41 [1.00]	1.23 [1.00]
TGM-B-EPU	1.67 [1.00]	1.56 [1.00]
TGM-B-GPR	1.51 [1.00]	1.27 [1.00]

Notes: Panel A: ADF includes a constant (lag length chosen by AIC); KPSS tests level stationarity (5% critical value 0.463); Q(10) and $Q^2(10)$ are Ljung-Box statistics on levels and squares; ARCH-LM uses 10 lags. Panel B: Ljung-Box Q(10) on standardized residuals z and on |z| for each model in Tables 4 and 5, with p-values in brackets. *** p < 0.01, ** p < 0.05, * p < 0.10.

The short-run parameters in Table 4 hardly change from one model to the next. Daily volatility reacts strongly to news, and the reaction fades slowly, so the short-run component carries much of the slow drift in rupee risk, including the unusual calm of 2024 to 2026. Once the long-run component is in place, a depreciation does not raise volatility much more than an appreciation of the same size. In equity markets, falling prices typically raise volatility more than rising ones, and investor fear is the usual explanation. The rupee's large moves have been policy decisions rather than panics, which may explain why that asymmetry is mostly absent here.

Table 4. Linear and Interaction GARCH-MIDAS Estimates

Parameter	GM-RV	GM-REM	GM-REM×EPU	GM-REM×GPR
μ	−0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)
α	0.432*** (0.052)	0.437*** (0.071)	0.423*** (0.032)	0.435*** (0.034)
β	0.506*** (0.026)	0.532*** (0.025)	0.513*** (0.023)	0.537*** (0.024)
γ	0.119 (0.119)	0.058 (0.163)	0.122** (0.059)	0.052 (0.059)
ν	3.303*** (0.118)	3.278*** (0.107)	3.293*** (0.116)	3.299*** (0.108)
m	−4.033* (2.155)	−3.863 (3.102)	−3.350*** (0.976)	−3.844*** (1.143)
θ	0.321*** (0.034)	0.087*** (0.010)	−2.165*** (0.238)	1.797*** (0.269)
ω	1.000 (bound)	3.291*** (0.913)	2.015*** (0.392)	2.230*** (0.553)
Log-likelihood	3,214.85	3,220.85	3,218.03	3,211.54
AIC	−6,413.7	−6,425.7	−6,420.1	−6,407.1
BIC	−6,366.1	−6,378.1	−6,372.4	−6,359.4
VR (%)	23.5	12.8	36.6	10.7

Notes: Student-t QMLE of Equations (3) to (6) with K = 12; 2,847 daily returns, 1 August 2014 to 27 February 2026. Robust standard errors in parentheses. γ applies to positive (depreciation) shocks. $VR = Var(ln\,\tau)/Var(ln\,\tau g)$. *** p < 0.01, ** p < 0.05, * p < 0.10.

Remittance growth raises long-run volatility, which supports H1. The effect is large: each additional point of weighted remittance growth raises long-run variance by about 9%. This runs against the stabilizing view and agrees with Lateef (2026) for Nigeria. Several features of Pakistan's remittance market make amplification plausible. A large share of the inflow comes from Saudi Arabia and the United Arab Emirates,

so it rises and falls with oil revenues and Gulf construction cycles rather than with conditions at home. Remittances also arrive in seasonal bursts around the two Eid festivals. And under a managed rate, a surge in dollar supply often signals the end of a period of pressure rather than a quiet addition to it, when senders who had been waiting for a better rate convert at once. Faster remittance growth thus tends to coincide with months in which the rupee is repricing.

Remittances also explain long-run volatility better than past volatility does. Under a managed rate, last month's volatility often reflects a single policy decision, such as a step devaluation, that tells little about what comes next. Remittances, by contrast, are a market flow that keeps arriving. It is therefore not surprising that they carry more information about next month's currency risk.

The interaction models fail a basic test of economic sense. The remittance effect is weakened by policy uncertainty in one model and strengthened by geopolitical risk in the other, and neither model fits better than remittances alone. Read literally, the EPU result says the rupee is calmer when remittance growth and policy uncertainty are both high or both low, and more volatile when they move apart. We can think of no mechanism that would produce this. The result also contrasts with the positive interaction effects Lateef (2026) reports. The regime estimates below explain the puzzle: the interaction term averages over periods in which remittances mattered in very different ways, and the sign it settles on depends on which periods happen to dominate each uncertainty index.

The first threshold model, without the break, seems at first to give a clean answer (Table 5). Above a fairly high level of policy uncertainty, the remittance effect disappears, and the test rejects a constant effect decisively. The natural headline would be that uncertainty switches the remittance channel off. That headline is wrong. The high-uncertainty months are almost entirely the period from May 2022 onwards, and a model that simply switches on that date, with no reference to uncertainty, fits almost as well and gives almost the same answer. The threshold is dating the crisis, not measuring uncertainty.

Table 5. Threshold GARCH-MIDAS Estimates with and without a May 2022 Break

Parameter	TGM-EPU	TGM-GPR	GM-REM-B	TGM-B-EPU	TGM-B-GPR
μ	0.001** (0.000)	0.000 (0.000)	0.001** (0.000)	0.001** (0.000)	0.001** (0.000)
α	0.485*** (0.036)	0.474*** (0.045)	0.484*** (0.036)	0.521*** (0.043)	0.504*** (0.039)
β	0.469*** (0.032)	0.493*** (0.027)	0.470*** (0.032)	0.415*** (0.042)	0.456*** (0.033)
γ	0.082 (0.056)	0.059 (0.090)	0.082 (0.060)	0.118* (0.064)	0.070 (0.059)
ν	3.196*** (0.113)	3.209*** (0.104)	3.195*** (0.112)	3.115*** (0.106)	3.102*** (0.110)
m	−3.362*** (0.650)	−2.677* (1.613)	−3.345*** (0.649)	−3.894*** (0.755)	−3.360*** (0.646)
θ (GM-REM-B)			0.276*** (0.021)		
θ_L	0.277*** (0.022)	0.305*** (0.036)		0.192*** (0.028)	0.279*** (0.022)

θ_H	−0.039 (0.045)	0.087*** (0.010)		0.290*** (0.017)	0.396*** (0.033)
δ_H	0.416 (0.384)	−1.184*** (0.420)		1.775*** (0.292)	−1.176*** (0.349)
δ_B			0.328 (0.512)	−0.687** (0.286)	1.468*** (0.361)
θ_B			−0.310*** (0.065)	−0.337*** (0.025)	−0.431*** (0.028)
ω	1.540*** (0.342)	2.706*** (0.427)	1.575*** (0.435)	1.000 (bound)	1.212*** (0.268)
Slope after May 2022 (θ_H + θ_B)			−0.034 (0.060)	−0.046** (0.020)	−0.035* (0.019)
Wald θ_L = θ_H	39.54***	38.81***		9.63***	18.93***
Threshold, index level	119.2	84.2		63.6	126.9
Threshold percentile	65th	15th		25th	75th
95% confidence set for threshold	106, 119	84, 87, 89, 101, 111		64	84, 87, 127
High-regime months	49 of 139	118 of 139		104 of 139	35 of 139
Log-likelihood	3,251.28	3,244.21	3,250.62	3,285.67	3,266.81
AIC	−6,482.6	−6,468.4	−6,481.2	−6,547.3	−6,509.6
BIC	−6,423.0	−6,408.9	−6,421.7	−6,475.9	−6,438.2
VR (%)	35.9	38.7	35.5	43.9	53.6
sup-LR (null model)	60.8 (GM-REM)	46.7 (GM-REM)	59.5 vs GM-REM	70.1 (GM-REM-B)	32.4 (GM-REM-B)
Bootstrap p-value [replications]	0.010 [99]	0.010 [99]		0.003 [299]	0.010 [100]
Bootstrap 95% critical value	9.61	9.15		10.94	9.48

Notes: Student-t QMLE, 2,847 daily returns (1 August 2014 to 27 February 2026). TGM has a threshold but no break, GM-REM-B has a break but no threshold, and TGM-B has both. Robust standard errors, conditional on the threshold, in parentheses. The confidence set lists grid thresholds within the 95% likelihood-ratio bound of Hansen (2000). A bootstrap p-value of 1/(replications + 1) means no bootstrap statistic exceeded the observed one. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

The preferred model therefore keeps the May 2022 break and asks whether an uncertainty threshold still matters once the crisis period is allowed to differ. Two results follow.

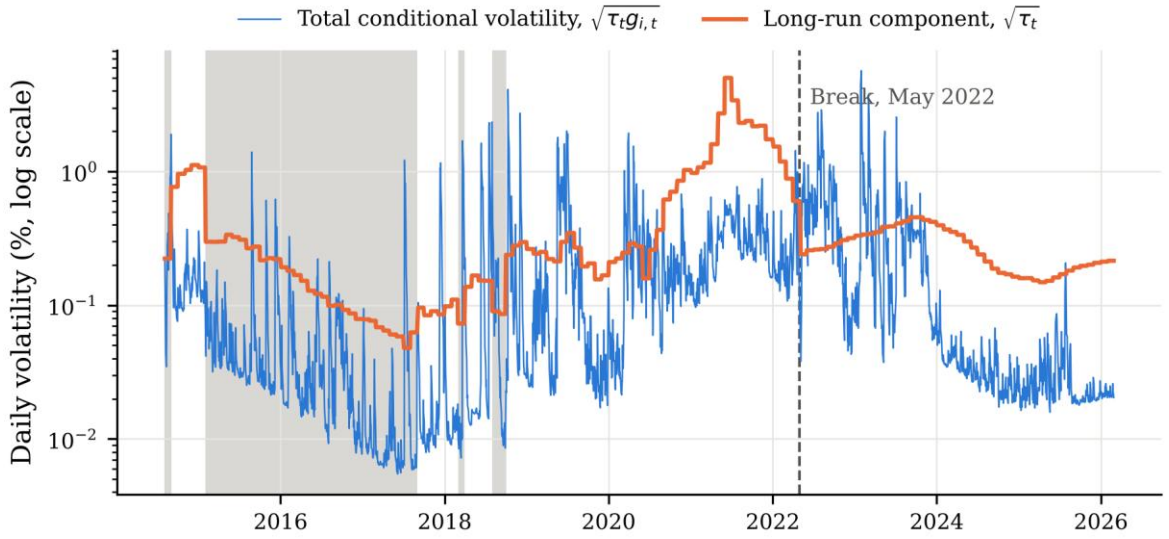
The first concerns the break. After May 2022, the remittance effect vanishes. The timing points to the way the rupee was managed. Through 2022 the informal cap on the interbank rate opened a wide gap with the open market, and a share of remittances is widely reported to have moved to hawala channels, where it never touched the interbank market. After the rates were unified in January 2023, the rupee settled under successive IMF programs into a period of near-fixity. In neither phase could remittance flows show up in the price. In one, they bypassed the formal market; in the other, the central bank absorbed them.

The second concerns the threshold. With the break in place, the boundary moves to a much lower level of policy uncertainty, a three-month EPU average of about 64, and it is sharply estimated. Above it, the remittance effect is roughly 50% larger than below it, and the test against the break-only model rejects a

single slope comfortably. High-uncertainty months are both more volatile in general and more sensitive to remittances, which supports H2 and H4. This matches Lateef (2026) in direction. When the policy outlook is unclear, the central bank has less room and less will to lean against every movement in dollar supply, and swings in remittances pass more directly into the rupee. Allowing for both the break and the threshold also triples the share of volatility explained by the long-run component, so these regimes are an important part of why rupee risk changes over time.

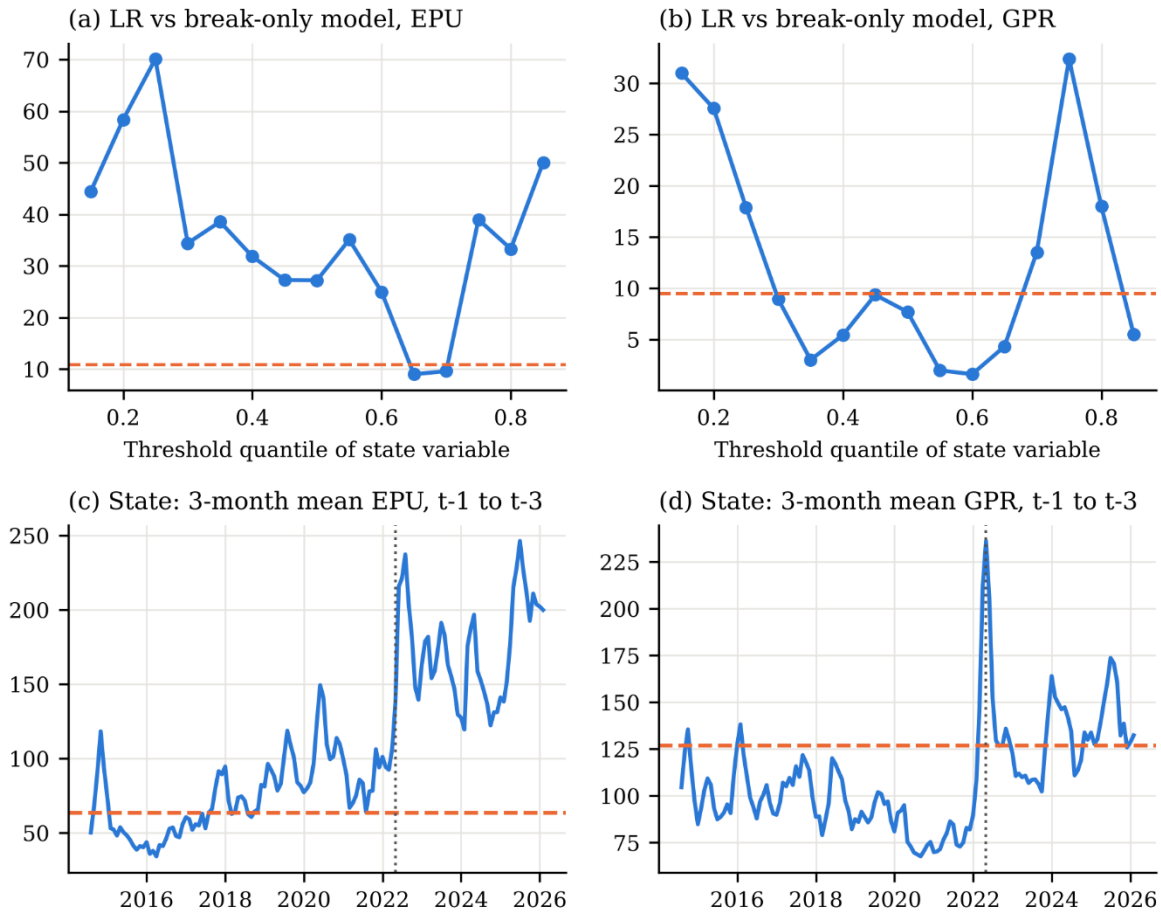
The economic size is large. Before May 2022, a typical rise in remittance growth roughly quadruples long-run variance in the low-uncertainty regime and increases it about eightfold in the high-uncertainty regime. Multiples of this size look implausible until one recalls how much the rupee's long-run volatility itself moved over the sample, from the near-silence of the peg years to the turmoil of the 2023 devaluation. Figure 2 shows the long-run and total volatility paths, and Figure 3 shows how sharply the fit depends on where the threshold is placed.

Figure 2. Total and Long-Run Conditional Volatility from the TGM-B Model (EPU State)



Notes: √(τg) and √τ (%, log scale), 1 August 2014 to 27 February 2026. Shaded months: low-EPU regime (EPU < 63.6). Dashed line: May 2022 break.

Figure 3. Threshold Profiles and Regime States (TGM-B)



Notes: (a, b) LR statistic against the break-only model by threshold percentile; dashed lines are bootstrap 95% critical values (10.9 for EPU, 9.5 for GPR). (c, d) Three-month mean EPU and GPR with estimated thresholds (63.6, 126.9) as dashed lines; the dotted line marks May 2022.

The identification problem has not gone away; it has moved. The months below the new threshold are almost exactly the 2015 to 2017 near-peg, when the SBP held the rupee close to 105 per dollar. A model that switches on the dates of the peg, without any uncertainty index, gives nearly the same remittance effects and fits nearly as well. Policy uncertainty was low during the peg and high afterward. The data cannot tell whether remittances began to matter more because uncertainty rose or because the SBP stopped holding the rate. We regard the second explanation as at least as plausible, and it accounts for all three periods in a single story. When the rate is held, reserves absorb swings in remittance inflows and the price does not move. When the rate is managed but allowed to adjust, those swings reach the price. When the rate is set administratively, or the inflow leaves the formal market, the link breaks again. On either reading, the remittance channel depends on the regime, but the regime is as much about the central bank as about uncertainty.

Geopolitical risk produces a fainter version of the same pattern, so H3 receives only partial support. The remittance effect is again larger when global risk is high. The high-risk months, however, fall mostly after

May 2022; the boundary between regimes is poorly determined, and the improvement in fit is about half that obtained with domestic policy uncertainty. A weaker link is what the economics would predict. Global geopolitical events reach Pakistan indirectly, through oil prices and Gulf labor markets (Bhatty et al., 2025; Lu et al., 2023; Privara et al., 2025), whereas domestic policy uncertainty bears directly on how the SBP manages the rate.

The robustness checks in Appendix Table A1 confirm the main pattern. A longer MIDAS window and the four-newspaper EPU index leave the threshold almost unchanged, and in both cases the remittance effect is larger in the high-uncertainty regime and disappears after the break. Estimating the model only on data before 2023, so that the break plays no role at all, gives the same threshold and the same ordering of effects. The result therefore does not depend on the crisis years.

Two checks narrow what the result can mean. When uncertainty is measured as a deviation from its recent trend rather than as a level, the ordering reverses: the remittance effect is smaller when uncertainty spikes above trend. Brief bursts of policy news do not strengthen the remittance channel. What matters is a sustained level of uncertainty, and in Pakistan that level is tied to a particular stretch of history. For geopolitical risk, the pre-2023 sample shows almost no difference between regimes, so the GPR result rests mainly on the post-2022 months. The remaining checks change nothing of substance. Letting each regime have its own lag profile adds little; the standardized residuals of every model show no remaining autocorrelation in levels or absolute values (Table 3, Panel B), and the Gaussian likelihood distorts the estimates in the way the fat tails would lead one to expect.

The forecasting comparison in Table 6 is sobering. No model forecasts significantly better than the simple remittance model at any horizon. The models that record lower losses on one measure do worse on the other. The reason lies in the evaluation window. From 2024, the SBP held the rupee almost fixed and realized volatility collapsed, so any model whose long-run component moves slowly kept predicting more volatility than occurred. A regime switch estimated on the past cannot anticipate a policy decision to freeze the rate. Regime dependence is clear in the fit of the models, but in a period dominated by a crisis and an administered recovery, it does not translate into better forecasts.

Table 6. Out-of-Sample Forecast Evaluation, January 2022 to February 2026

Model	QLIKE h=10	DM	MSE h=10	DM	QLIKE h=20	DM	MSE h=20	DM	QLIKE h=30	DM	MSE h=30	DM
GM-REM	26.04	—	214.3	—	21.43	—	757.5	—	23.90	—	1,512.3	—
GM-RV	4.11	−1.58	1,443.0	1.02	3.91	−1.89*	5,597.7	1.01	4.09	−1.85*	12,342.7	1.01
GM-REM×EPU	1.88	−1.66*	267.7	2.34**	1.82	−1.85*	1,350.7	1.91*	1.82	−1.74*	4,127.2	1.61
GM-REM×GPR	18.89	−1.26	220.1	0.69	16.59	−1.48	796.5	0.90	19.41	−1.68*	1,633.9	0.97

TGM-EPU	29.18	1.32	238.6	1.29	22.41	1.14	849.3	1.25	23.40	−0.49	1,695.6	1.19
TGM-GPR	24.88	−1.27	216.3	1.37	20.61	−1.42	764.1	0.95	23.29	−1.32	1,522.4	0.55

Notes: Forecasts of cumulative variance over the next h trading days, from models re-estimated every six months on an expanding window. Losses are averages of QLIKE (Patton, 2011) and MSE against realized variance. DM is the Diebold-Mariano statistic with the Harvey et al. (1997) correction, relative to GM-REM; negative values favor the listed model. Break models are excluded. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

These results fit into the literature in a clear way. The positive average effect of remittances on volatility matches Lateef (2026) for Nigeria and contradicts the stabilizing view of remittances. The role of uncertainty is consistent with evidence that policy and geopolitical uncertainty raise currency volatility (Aftab et al., 2024; Ekeocha et al., 2025; Salisu et al., 2022; Wei et al., 2025), and the better fit once regimes are allowed mirrors Segnon et al. (2024). The interaction effects pull in opposite directions, which a linear interaction approach cannot easily explain. Global geopolitical risk plays a weak and unstable role, closer to Yilmazkuday (2025) mixed findings than to uniform amplification.

The study also goes a step further than this literature by asking what the regimes represent. In Pakistan, policy uncertainty and the way the exchange rate is managed have moved together so closely that the data cannot separate them. A regime that looks like an uncertainty regime may be an exchange rate regime. Studies that treat the exchange rate arrangement as fixed risk attributing to uncertainty an effect that belongs to the central bank.

4. Conclusion

This paper asks whether remittances steady the Pakistani rupee or add to its swings, and whether their effect changes between regimes rather than rising or falling smoothly with uncertainty. Using daily official PKR/USD rates from August 2014 to February 2026, monthly remittances, Pakistan's EPU index and the global GPR index, we estimate linear and interaction GARCH-MIDAS benchmarks alongside a threshold GARCH-MIDAS model with a structural break in May 2022. Faster remittance growth raises long-run exchange rate volatility on average, in line with the Nigerian evidence. The effect is far from constant. It disappears after May 2022, and before that it is about half as large again when policy uncertainty is high.

The central finding concerns what these regimes represent. The low-uncertainty months are almost exactly the 2015 to 2017 near-peg, and a model built on the dates of the peg fits nearly as well as one built on uncertainty. In Pakistan, policy uncertainty and the management of the exchange rate have moved together too closely for the data to separate them. Geopolitical risk shows a fainter version of the same pattern. Interaction terms mix these regimes and produce signs that change with the choice of index, and no model forecasts better than the simple remittance benchmark.

These results qualify the standard view of remittances as a stabilizing inflow. Remittances can smooth the supply of dollars only when they pass through formal channels and are sold at a market price. Under a peg, reserves absorb them. Under an administered rate with a wide open-market premium, part of the flow

leaves the formal market altogether. The remittance channel therefore depends on the exchange rate arrangement, and uncertainty indices may simply proxy for that arrangement.

For the State Bank of Pakistan, the practical lesson is about when remittance data carry information. Under a managed float, swings in remittance growth feed into long-run currency risk and belong in exchange rate monitoring and reserve planning. When the rate is held or set administratively, that link weakens. Keeping the interbank and open-market rates close, as the 2023 unification eventually did, keeps remittances in formal channels. Importers and others with dollar exposure can read remittance growth the same way: as a useful signal of currency risk when the rupee is allowed to move, and a weak one when it is held.

The study has clear limits. The EPU index ends in January 2026. The break date was chosen with knowledge of the crisis, and the uncertainty regimes cannot be separated from episodes of exchange rate management. The model identifies a regime-dependent association rather than a causal effect, and the conversion-market mechanism is inferred rather than tested. Using the open-market premium or SBP intervention as the threshold variable would test that mechanism directly. A panel of large recipients with different exchange rate regimes, such as Bangladesh, Egypt and the Philippines, would show whether the pattern reflects uncertainty or central bank practice.

Remittances matter for rupee risk, but only under some arrangements, and more so when uncertainty is high.

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Appendix A

Table A1. Robustness of the Threshold GARCH-MIDAS Results

Specification	State	Threshold	θ_L	θ_H	θ_B	LR	High months
TGM-B, 24-month MIDAS window	EPU	63.6	0.218*** (0.032)	0.362*** (0.025)	−0.436*** (0.027)	100.1	104/139
TGM-B, four-newspaper EPU (from Apr 2015)	EPU4	62.5	0.163*** (0.031)	0.281*** (0.016)	−0.327*** (0.026)	89.9	98/131
TGM-B, Gaussian QMLE	EPU	63.6	−0.077*** (0.028)	0.022 (0.014)	−0.094*** (0.027)	190.4	104/139
TGM-B, detrended EPU state	EPU dev.	0.065	0.270*** (0.037)	0.151*** (0.040)	−0.326*** (0.031)	22.6	76/139
TGM, sample ends Dec 2022	EPU	63.8	0.198*** (0.026)	0.276*** (0.015)	—	89.6	65/101
TGM, sample ends Dec 2022	GPR	79.0	0.264*** (0.049)	0.243*** (0.026)	—	36.4	85/101
Calendar regime: near-peg Jan 2015–Nov 2017 + break	Peg dates	—	0.194*** (0.028)	0.286*** (0.021)	−0.332*** (0.028)	62.7	104/139
TGM, regime-specific weights	EPU	119.2	0.275*** (0.022)	0.047*** (0.015)	—	6.9 (vs common ω)	49/139
TGM, regime-specific weights	GPR	84.2	0.306*** (0.035)	0.085*** (0.009)	—	1.8 (vs common ω)	118/139
TGM, regime-specific weights	EPU dev.	0.065	0.021 (0.014)	0.107*** (0.017)	—	0.1 (vs common ω)	76/139

Notes: Each row changes one element of Table 5. LR is twice the log-likelihood gain over the null model estimated on the same sample: GM-REM-B for the TGM-B rows and the calendar regime, and GM-REM for the TGM rows. In the regime-specific-weights rows, LR instead compares with the same model with a common ω. Thresholds are in index units, except for the detrended state (log deviation from a 24-month moving average). Robust standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$