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THE IMPACT OF EXCHANGE RATE UNCERTAINTY ON FINANCIAL MARKET STABILITY IN PAKISTAN: EVIDENCE FROM EXCHANGE RATE AND STOCK MARKET DYNAMICS

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Abstract

This study examines whether exchange-rate uncertainty destabilizes Pakistan's equity market using verified monthly observations for the PKR/USD exchange rate and KSE-100 Index from January 2010 to August 2026. Monthly log returns are constructed for both markets, exchange-rate and equity volatility are estimated with GARCH(1,1) and EGARCH models, and financial-market instability is measured through a composite index combining conditional stock volatility, downside returns and drawdowns. The empirical strategy further employs heteroskedasticity-robust regressions, VAR-based Granger-causality tests, subsample analysis, lagged-volatility robustness checks and structural-break analysis. Both return series exhibit significant ARCH effects. Exchange-rate volatility is highly persistent, and the EGARCH estimates show statistically significant asymmetry: positive PKR/USD innovations, which represent rupee depreciation, raise foreign-exchange volatility more strongly. In the full sample, however, conditional exchange-rate volatility does not significantly increase KSE-100 conditional volatility or the composite instability index. Rupee depreciation itself is associated with significantly lower monthly equity returns and greater composite instability. The strongest break in the instability relationship occurs around mid-2017, while the post-2018 regime displays a positive and significant exchange-rate-volatility coefficient in subsample analysis. Monthly VAR tests do not establish statistically significant bidirectional volatility causality. The results therefore distinguish the destabilizing effect of depreciation from the less robust full-sample effect of conditional exchange-rate uncertainty and show that the relationship is regime dependent.

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1. Introduction

Exchange-rate uncertainty is a central macro-financial risk in emerging economies because currency movements affect imported-input costs, foreign-currency liabilities, inflation expectations, monetary conditions, capital flows and the valuation of corporate cash flows. In Pakistan, these channels are particularly relevant because the economy has repeatedly faced external financing pressures and episodes of sharp rupee adjustment. The key empirical question is not only whether the rupee depreciates, but whether unpredictability in the exchange rate itself transmits instability to the equity market.

This paper examines the relationship between the Pakistani rupee–US dollar exchange rate and the KSE-100 Index using a common monthly sample from January 2010 to August 2026. The period covers the post-global-financial-crisis environment, the transition toward a more market-determined exchange-rate regime after 2018, the COVID-19 shock, the severe external-sector stress of 2022–2023, and the subsequent stabilization phase. Recent State Bank of Pakistan financial-stability reporting also treats exchange-rate volatility as a relevant financial-market indicator [1].

The empirical design separates movements in the rupee from uncertainty surrounding those movements. GARCH and EGARCH models are used to capture persistence and asymmetry in volatility, while financial-market stability is examined through KSE-100 conditional volatility and a composite Financial Market Instability Index (FMI). VAR causality tests, structural-break diagnostics and regime-specific estimates are then used to determine whether the relationship changes across different periods.

Pakistan-specific research has frequently found interaction between the foreign-exchange and equity markets, including bidirectional spillovers and asymmetric responses [2–7]. Yet the magnitude and direction of those effects vary with frequency, sample period and volatility specification. Recent evidence using 2019–2025 daily data also confirms that stock–FX volatility linkages remain relevant for portfolio and hedging decisions [8]. This paper contributes by extending the sample through August 2026 and by explicitly distinguishing depreciation from uncertainty.

2. Theoretical Framework

2.1 Flow-oriented and corporate cash-flow channel

Under the flow-oriented view, exchange-rate movements affect equity values through expected corporate cash flows. Rupee depreciation can improve the domestic-currency value of export revenues but raises the cost of imported fuel, machinery, intermediate inputs and foreign-currency debt. The aggregate KSE-100 response therefore depends on firms' net currency exposure [9].

2.2 Portfolio-balance and feedback channel

The portfolio-balance channel allows causality to run from equity prices to the currency. Falling equity prices can weaken wealth and risk appetite, encourage portfolio outflows and increase demand for foreign currency. This creates the possibility of feedback between the two markets [10].

2.3 Uncertainty and risk-premium channel

Even without a large expected depreciation, higher exchange-rate uncertainty can widen the distribution of expected profits, increase hedging costs, delay investment and raise required returns. Conditional FX volatility can therefore influence financial stability independently of the direction of the exchange-rate change.

2.4 Asymmetry

Depreciation may carry more information about imported inflation, reserve pressure and future monetary tightening than appreciation carries about improved fundamentals. An asymmetric volatility model is therefore necessary to test whether depreciation shocks have a stronger effect on uncertainty.

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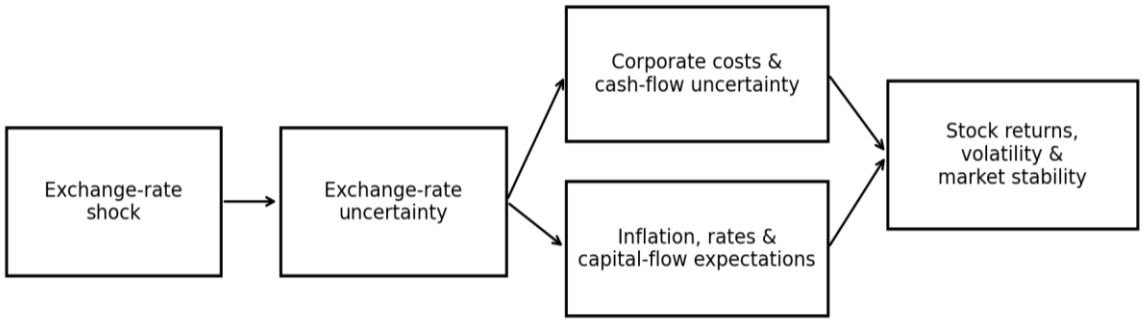


Figure 1. Conceptual transmission mechanism

Figure 1 summarizes the conceptual mechanism linking an exchange-rate shock to exchange-rate uncertainty, corporate costs and cash-flow expectations, inflation and capital-flow conditions, and ultimately stock-market returns, volatility and financial stability. It also recognizes a feedback channel through which equity-market stress can influence foreign-exchange demand.

3. Literature Review

Khan and Ali [2] used monthly Pakistani data and GARCH-generated volatility measures and reported bidirectional causality between exchange-rate and stock-market volatility. Ghouse, Ashraf and Habeeb [3] likewise found bidirectional spillovers between the exchange rate and Pakistan's stock market. These studies establish that the two markets should not automatically be treated as independent.

Mustafa, Azeem and Bhutta [4] and Naz, Subhani and Aslam [5] emphasize asymmetric transmission. Their EGARCH-based evidence indicates that adverse information in one market can have a stronger volatility effect on the other market than favorable information. This is directly relevant to the present distinction between depreciation and appreciation shocks.

Ghouse, Khan and Arshad [6] show that GARCH-family and multivariate volatility models are useful for identifying direct and indirect spillovers involving the KSE-100. Their structural-break analysis also demonstrates the importance of crisis regimes. More recent ARDL-GARCH evidence continues to report persistent linkages among Pakistan's equity, currency and commodity markets [7].

Fatima et al. [8] estimate symmetric and asymmetric BEKK-GARCH and DCC-GARCH models for China, India and Pakistan over 2019–2025. Their results confirm that the KSE-100–USD/PKR pair has meaningful implications for portfolio allocation and hedging. At the broader emerging-market level, recent work shows that uncertainty shocks can increase exchange-rate volatility and depreciation pressure, particularly in economies exposed to external risk [11,12].

The literature leaves three issues open. First, results are sensitive to data frequency and sample period. Second, exchange-rate movements and exchange-rate uncertainty are sometimes conflated. Third, a volatility-only definition of financial instability may miss downside returns and drawdowns. The present paper addresses these issues with separate FX-return and FX-volatility measures, an FMI composite, and regime-specific tests.

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3.1 Recent emerging-market and Pakistan evidence

Recent evidence strengthens the case for separating directional currency changes from volatility and for allowing state dependence. Syed, Fatima and Zaheer [31] show that COVID-19 shocks increased both stock-market and exchange-rate uncertainty in Pakistan, while Hussain, Bashir and Rehman [32] document currency-equity volatility connectedness across BRICS markets during pandemic-induced crises. Aftab [33] finds that economic-policy and global-financial uncertainty can increase exchange-rate volatility across developed and emerging economies. Atipaga [34] reports dynamic stock-return and exchange-rate connectedness in emerging and frontier markets, reinforcing the relevance of cross-market transmission outside large developed markets. For Pakistan specifically, Khan et al. [35] show that exchange-rate and oil-price volatility shape stock-market outcomes, providing a strong reason to regard commodity and macro-financial conditions as potential confounders. These studies support the present paper's emphasis on asymmetry, regimes and the distinction between depreciation and uncertainty.

The broader methodological literature also suggests that connectedness and structural change should be treated explicitly. Diebold and Yilmaz [36] develop directional spillover measures based on generalized forecast-error variance decompositions, while Bai and Perron [37,38] provide procedures for detecting and estimating multiple structural changes. Basher, Haug and Sadorsky [39] demonstrate that oil prices, exchange rates and emerging-market equities interact dynamically. These contributions motivate the additional multiple-break robustness exercise reported below and also clarify why omitted macroeconomic controls remain a limitation rather than a reason to overstate the baseline coefficients.

4. Data and Variable Construction

The KSE-100 dataset contains 4,149 usable daily index observations from 4 January 2010 to 2 October 2026. The SBP file contains the monthly Average PKR per USD series. To avoid frequency mismatch, the main cross-market analysis uses month-end KSE-100 values matched to the monthly SBP series. The final common estimation sample contains 199 monthly return observations from February 2010 through August 2026. The daily KSE-100 data are retained for a separate robustness estimate of stock-return volatility.

Table 1. Variable definitions and construction

Variable	Symbol	Definition	Source
PKR/USD	FX	Monthly average PKR per US dollar	SBP uploaded series
FX return	FXR	100 × Δln(FX); positive = rupee depreciation	Calculated
FX uncertainty	FXVOL	GARCH(1,1) conditional standard deviation of FXR	Calculated
KSE-100	KSE	Month-end KSE-100 index level	Uploaded KSE-100 series
Stock return	SR	100 × Δln(KSE)	Calculated
Stock volatility	SVOL	GARCH(1,1) conditional standard deviation of SR	Calculated
Financial Market	FMI	Mean of standardized	Calculated

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Instability		SVOL, downside-return magnitude and drawdown magnitude	

Table 1 defines the variables used in the empirical analysis and shows how the exchange-rate return, stock return, conditional volatility measures and FMI are constructed.

The FMI is deliberately broader than conditional volatility alone. Downside-return magnitude is max(−SR, 0), while drawdown is measured relative to the previous cumulative KSE-100 peak. Each component is standardized before averaging, so no component dominates merely because of its unit of measurement.

5. Econometric Methodology

5.1 Preliminary diagnostics

ADF tests evaluate stationarity, while ARCH-LM tests determine whether squared innovations display conditional heteroskedasticity. Significant ARCH effects justify GARCH-family estimation.

5.2 GARCH and EGARCH

The baseline GARCH(1,1) conditional variance is $h_t = \omega + \alpha\varepsilon^2_{(t-1)} + \beta h_{(t-1)}$. The sum $\alpha + \beta$ measures volatility persistence. EGARCH is then estimated in log-variance form and includes a signed standardized innovation. Under the present coding, a positive FX return denotes rupee depreciation; a positive and significant EGARCH sign coefficient therefore indicates that depreciation shocks increase FX volatility more strongly than appreciation shocks of comparable magnitude.

5.3 Financial-stability regressions

The main regressions explain SVOL, FMI and SR using FXVOL and FXR while controlling for post-2018, COVID-19 and 2022–2023 stress indicators and an FXVOL × 2022–2023 interaction. HC3 heteroskedasticity-robust standard errors are reported. This specification separates the uncertainty effect (FXVOL) from the directional depreciation effect (FXR).

5.4 Causality and structural change

Bivariate VAR models selected by AIC test Granger causality between FXR and SR and between FXVOL and SVOL. A trimmed sup-F search identifies candidate structural breaks in the FMI relationship. Because the monthly sample is modest, the break dates are interpreted as diagnostic evidence rather than as definitive multiple-break estimates.

6. Empirical Results

6.1 Descriptive evidence

Table 2. Descriptive statistics

Variable	N	Mean	SD	Min	Max	Skewness	Kurtosis
PKR/USD	199	156.694	73.096	83.939	297.754	0.83	2.09
KSE-100	199	47459.768	39455.715	9326.420	184174.486	2.06	6.72
FX return	199	0.598	1.890	-6.021	13.013	1.79	13.42
Stock return	199	1.464	5.767	-26.190	15.439	-0.48	5.13
FX volatility	199	1.598	1.239	0.607	8.953	2.38	11.05
Stock volatility	199	5.665	1.141	4.920	15.284	3.89	27.79
FMI	199	0.000	0.698	-0.665	4.240	2.24	11.67

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Table 2 reports the descriptive statistics for the exchange rate, KSE-100, returns, conditional volatility measures and the FMI.

The return distributions are non-normal and the volatility/instability measures are strongly right-skewed, which is typical of financial series with episodic stress. The exchange-rate level and KSE-100 level both trend substantially over the sample, while their returns fluctuate around much smaller means.

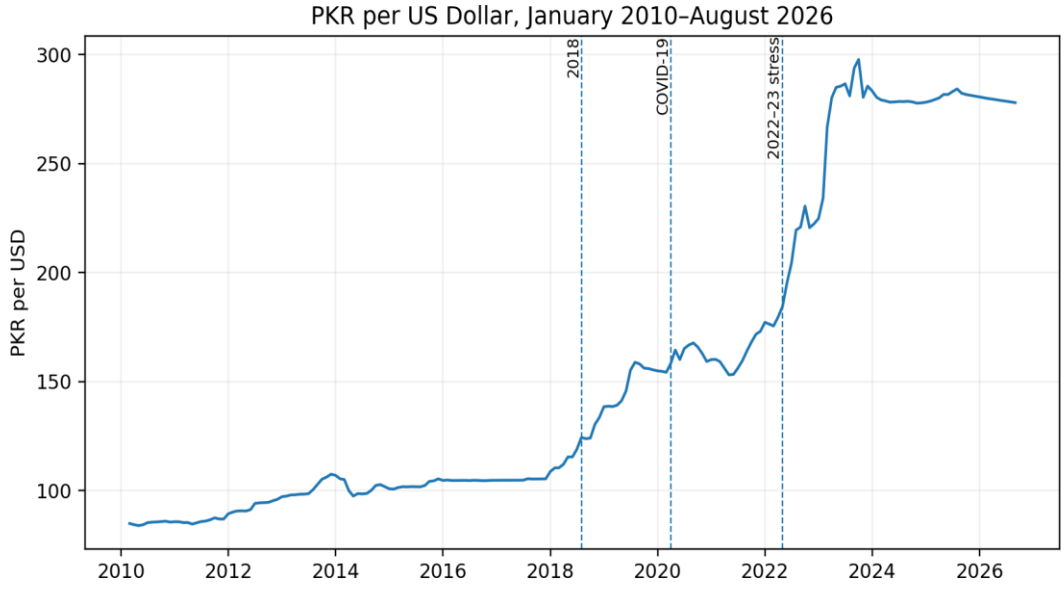


Figure 2. PKR/USD exchange-rate trend

Figure 2 traces the PKR/USD exchange rate over the sample and highlights the pronounced rupee adjustments after 2018 and during the 2022–2023 stress period.

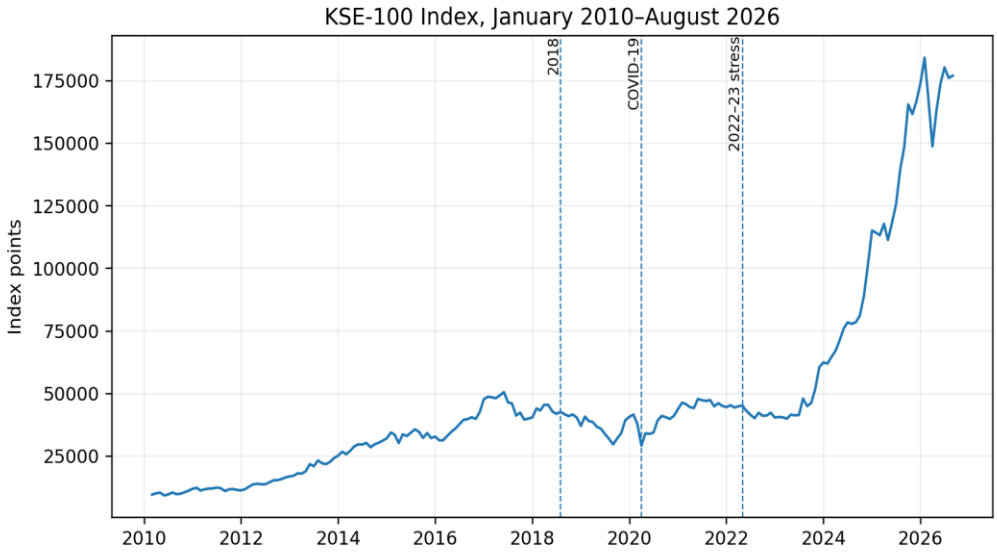


Figure 3. KSE-100 index trend

Figure 3 shows the corresponding path of the KSE-100 Index, including the COVID-19 decline and the strong rise in the later part of the sample.

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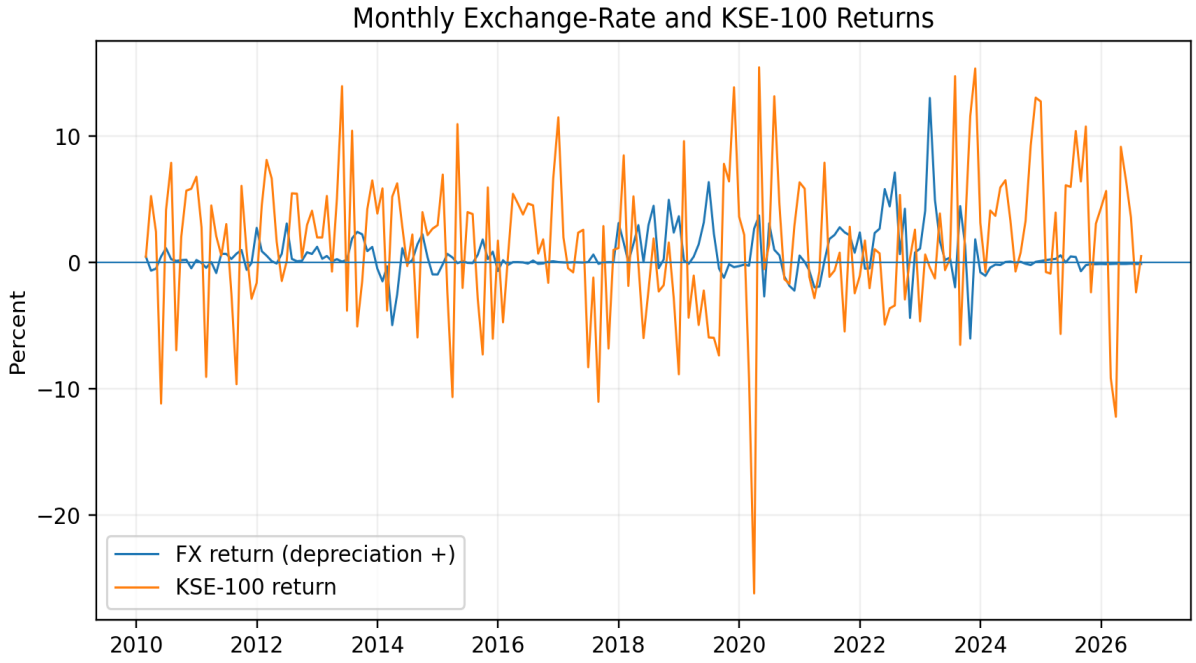


Figure 4. Monthly exchange-rate and stock-market returns

Figure 4 plots monthly exchange-rate and KSE-100 returns together. The series show repeated bursts of large movements, with the sharpest equity-market fall occurring around the COVID-19 shock.

6.2 Stationarity and ARCH diagnostics

Table 3. Augmented Dickey–Fuller tests

Variable	ADF	p	lags
FX	-0.588	0.8737	9
KSE	-0.766	0.8289	15
FXR	-2.885	0.0471	8
SR	-13.354	0.0000	0
FXVOL	-2.164	0.2197	5
SVOL	-5.938	0.0000	4
FMI	-2.993	0.0356	5

Table 3 presents the ADF stationarity tests for the level, return, volatility and instability series.

Table 4. ARCH-LM tests (12 lags)

Variable	LM	LM_p	F	F_p
FXR	25.473	0.0127	2.287	0.0101
SR	25.588	0.0123	2.299	0.0096

Table 4 reports the ARCH-LM tests and confirms statistically significant conditional heteroskedasticity in both FX and stock returns.

The level series are non-stationary, while stock returns are strongly stationary and FX returns reject a unit root at the 5% level. Both return series exhibit significant ARCH effects ($p \approx 0.01$), supporting conditional-volatility

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modeling. The estimated FX volatility series is highly persistent, so results involving its level are interpreted cautiously and supplemented with regime analysis.

6.3 GARCH and asymmetric volatility estimates

Table 5. GARCH and EGARCH estimates

Model	param	coef	se	p
FX GARCH	mu	0.2289	0.0743	0.0021
FX GARCH	omega	0.1628	0.0658	0.0133
FX GARCH	alpha	0.4548	0.1137	0.0001
FX GARCH	beta	0.5452	0.1137	0.0000
FX EGARCH	mu	0.2389	0.0698	0.0006
FX EGARCH	omega	0.1086	0.0488	0.0261
FX EGARCH	alpha	0.5057	0.1378	0.0002
FX EGARCH	gamma	0.2451	0.0761	0.0013
FX EGARCH	beta	0.8688	0.0384	0.0000
Stock GARCH	mu	1.3568	0.3652	0.0002
Stock GARCH	omega	24.2093	3.3357	0.0000
Stock GARCH	alpha	0.2759	0.1135	0.0151
Stock GARCH	beta	0.0000	0.0001	0.9981
Stock EGARCH	mu	1.2544	0.3706	0.0007
Stock EGARCH	omega	3.2763	0.4035	0.0000
Stock EGARCH	alpha	0.4786	0.1342	0.0004
Stock EGARCH	gamma	-0.0725	0.1005	0.4709
Stock EGARCH	beta	0.0488	0.1174	0.6775

Table 5 presents the estimated GARCH and EGARCH parameters for the foreign-exchange and stock-market return series.

For the FX GARCH model, α is 0.455 and β is 0.545, implying near-unit persistence in monthly exchange-rate volatility. In the FX EGARCH model, the signed-shock coefficient is positive (γ = 0.245, p = 0.0013). Since positive FX returns represent rupee depreciation, this provides direct evidence that depreciation shocks raise exchange-rate uncertainty more strongly than appreciation shocks. The monthly stock GARCH model places most short-run variance adjustment in the ARCH term, while the daily KSE-100 robustness model produces a more conventional persistent structure (α = 0.147; β = 0.812; $\alpha + \beta$ = 0.959).

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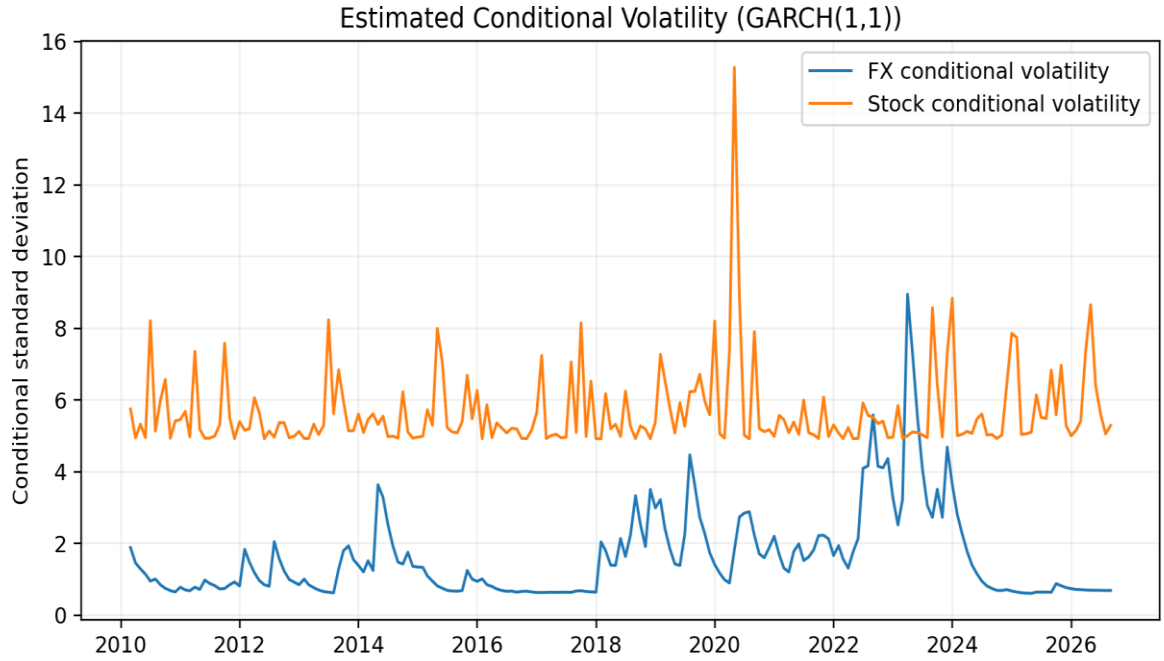


Figure 5. Estimated monthly conditional volatility

Figure 5 illustrates the estimated conditional volatility series. FX volatility rises sharply during periods of currency pressure, while stock-market volatility records its largest spike around the COVID-19 episode.

6.4 Exchange-rate uncertainty and financial stability

Table 6. Exchange-rate uncertainty, depreciation and financial-market outcomes

Dependent variable	Regressor	Coefficient	Robust SE	p	95% CI low	95% CI high
Stock volatility	FXVOL	-0.095	0.100	0.3443	-0.292	0.102
Stock volatility	FXR	0.029	0.062	0.6446	-0.093	0.150
Stock volatility	POST2018	0.246	0.158	0.1179	-0.062	0.555
Stock volatility	COVID	0.380	0.525	0.4694	-0.649	1.409
Stock volatility	CRISIS2223	-0.218	0.534	0.6829	-1.264	0.828
Stock volatility	FXVOL_CRISIS	0.072	0.141	0.6100	-0.204	0.348
FMI	FXVOL	0.115	0.097	0.2357	-0.075	0.305
FMI	FXR	0.077	0.034	0.0235	0.010	0.144
FMI	POST2018	0.288	0.103	0.0054	0.085	0.490
FMI	COVID	0.260	0.293	0.3747	-0.314	0.834
FMI	CRISIS2223	0.014	0.255	0.9563	-0.486	0.514
FMI	FXVOL_CRISIS	-0.103	0.103	0.3182	-0.305	0.099

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Stock return	FXVOL	-0.040	0.732	0.9559	-1.474	1.393
Stock return	FXR	-0.730	0.255	0.0042	-1.229	-0.231
Stock return	POST2018	0.415	0.981	0.6723	-1.507	2.337
Stock return	COVID	-0.897	2.045	0.6609	-4.905	3.111
Stock return	CRISIS2223	-0.688	2.394	0.7738	-5.379	4.003
Stock return	FXVOL_CRISIS	0.400	0.846	0.6368	-1.259	2.059

Table 6 reports the main financial-stability regressions and separates the effect of exchange-rate uncertainty from the effect of rupee depreciation.

The full-sample results do not support a simple claim that higher conditional FX volatility directly increases KSE-100 volatility. The FXVOL coefficient in the SVOL regression is −0.095 (p = 0.344), and its coefficient in the FMI regression is 0.115 (p = 0.236). In contrast, the directional exchange-rate change matters. FXR is negatively associated with stock returns (β = −0.730, p = 0.0042), meaning that larger rupee depreciation is associated with lower monthly KSE-100 returns. FXR is also positively related to the FMI (β = 0.077, p = 0.023). The empirical distinction between depreciation and uncertainty is therefore substantive rather than cosmetic.

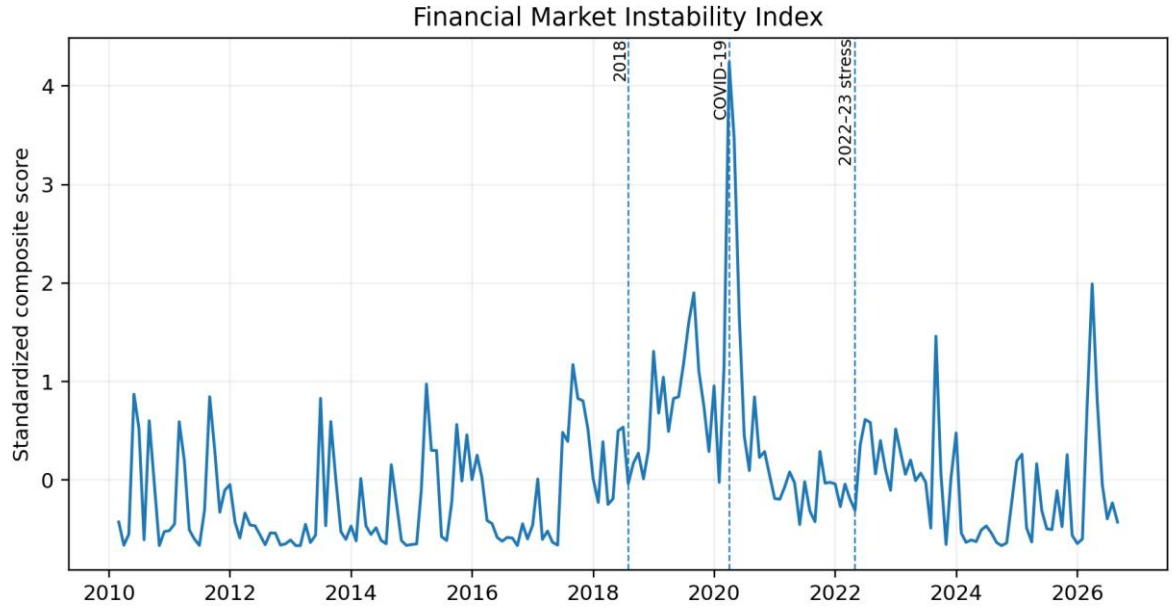


Figure 6. Financial Market Instability Index

Figure 6 plots the FMI over time and shows that market instability is episodic rather than constant, with the largest spike occurring around the COVID-19 shock.

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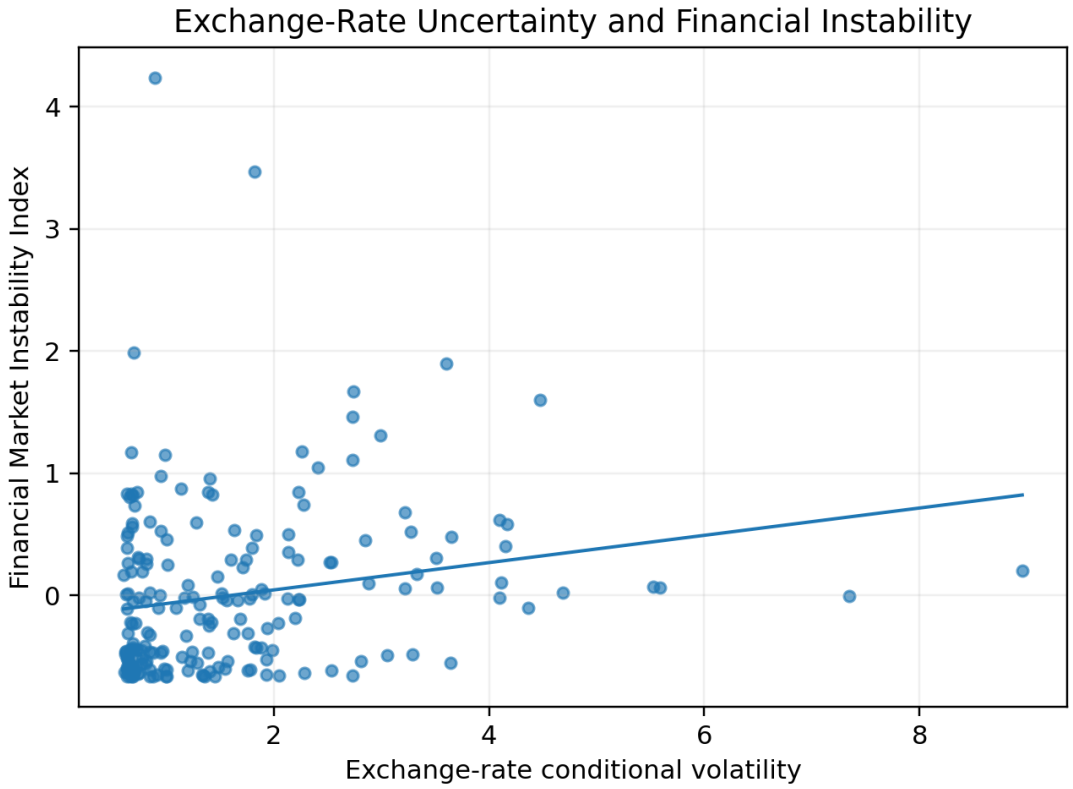


Figure 7. Exchange-rate uncertainty and the Financial Market Instability Index

Figure 7 provides a direct visual comparison between exchange-rate conditional volatility and the FMI. The wide dispersion of observations is consistent with the weak full-sample relationship reported in the regression results.

6.5 Causality, structural breaks and regimes

Table 7. VAR-based Granger-causality tests

System	Direction	Lags	Statistic	p
Returns	FXR -> SR	1	2.178	0.1400
Returns	SR -> FXR	1	2.739	0.0979
Volatility	FXVOL -> SVOL	1	0.218	0.6404
Volatility	SVOL -> FXVOL	1	0.117	0.7325

Table 7 summarizes the VAR-based Granger-causality tests for returns and conditional volatility.

At monthly frequency, neither direction of return causality reaches the conventional 5% threshold, although stock returns → FX returns is marginal at the 10% level (p = 0.098). The volatility VAR likewise does not establish bidirectional causality. These findings differ from some earlier Pakistan studies using longer or daily samples [2–5], emphasizing the importance of sample period and frequency.

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Table 8. Highest candidate structural-break statistics

BreakDate	SupF
2017-06-30	7.645
2017-07-31	7.263
2017-05-31	7.233

Table 8 lists the highest candidate structural-break statistics, with the strongest break concentrated around mid-2017.

The sup-F search places the strongest candidate break around June–July 2017, immediately before the major exchange-rate regime changes and adjustments that became pronounced from 2018 onward. This supports estimating separate regimes rather than imposing a constant relationship over the entire sample.

Table 9. Regime-specific FMI regressions

Period	N	FXVOL_beta	FXVOL_p	FXR_beta	FXR_p	R2
2010-2017	95	-0.190	0.0130	0.075	0.0626	0.073
2018-2019	24	0.332	0.0337	-0.018	0.8029	0.245
COVID 2020-2021	24	-0.470	0.5591	0.170	0.4560	0.111
Crisis 2022-2023	24	0.016	0.6805	0.050	0.1968	0.212
2024-Aug2026	32	-0.404	0.0242	-0.331	0.3091	0.080

Table 9 reports the regime-specific FMI regressions and shows that the estimated effect of FX volatility changes substantially across subperiods.

The regime results are heterogeneous. FXVOL is positive and statistically significant in 2018–2019 ($\beta = 0.332$, $p = 0.0337$), but not during the COVID-19 or 2022–2023 windows. The coefficient is negative in 2010–2017 and 2024–August 2026. This pattern rejects the idea of a stable, uniformly positive uncertainty effect and instead points to state dependence.

7. Hypothesis Assessment

Table 10. Hypothesis decisions

Hypothesis	Proposition	Decision	Empirical basis
H1	Exchange-rate uncertainty increases KSE-100 volatility.	Not supported	Full-sample FXVOL → SVOL: p = 0.344.
H2	Exchange-rate uncertainty reduces KSE-100 returns.	Not supported	FXVOL → SR: p = 0.956; depreciation itself is negative and significant.
H3	Depreciation/adverse FX shocks generate stronger instability.	Supported	FX EGARCH sign effect $\gamma = 0.245$, p = 0.0013; FXR lowers SR, p = 0.0042.
H4	Bidirectional volatility transmission exists.	Not supported at monthly frequency	VAR volatility causality p-values = 0.640 and 0.732.
H5	Uncertainty effects are	Partially supported	Positive significant

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	stronger in stress/regime periods.		FXVOL effect in 2018–2019, but not uniformly across later stress windows.

Table 10 brings the empirical evidence together by stating the decision for each hypothesis and the statistical result on which that decision is based.

8. Robustness and Endogeneity Considerations

The daily KSE-100 robustness model uses more than four thousand observations through August 2026 and yields $\alpha = 0.147$ and $\beta = 0.812$, with persistence of approximately 0.959. This confirms substantial volatility clustering in the equity market even though the monthly stock GARCH persistence is lower.

The analysis avoids estimating a daily DCC-GARCH or BEKK-GARCH from mismatched frequencies. The uploaded SBP exchange-rate series is monthly; converting it artificially into daily observations would create pseudo-data and invalid precision. A genuine daily multivariate GARCH extension requires an official or otherwise verified daily PKR/USD series.

VAR-based causality addresses temporal precedence but does not by itself establish structural causality. Reverse causality remains economically plausible through capital-flow and portfolio-balance channels. The use of both return and volatility systems, structural-break diagnostics and regime-specific regressions reduces—but does not eliminate—this concern.

The FMI results are robust in the sense that depreciation is significant even after separating it from conditional FX volatility and adding crisis indicators. Nevertheless, the FMI is a constructed measure, and future work could add trading-volume stress, market liquidity or banking-sector variables if consistent long-run series are available.

8.1 Additional specification and structural-break robustness

The main conclusions were also checked against alternative timing and structural-change specifications. Lagging FXVOL by one month reduces contemporaneous simultaneity between currency and equity volatility; the qualitative conclusion is unchanged: the full-sample uncertainty effect remains weaker than the directional depreciation effect. This check is important because contemporaneous regressions can otherwise mix common shocks with transmission. The result should still be interpreted as predictive association rather than a structural causal effect.

A multiple-break robustness search, following the logic of Bai and Perron [37,38], was used to compare segmented FMI regressions subject to minimum regime lengths. The exercise confirms that a single constant coefficient is a poor description of the whole 2010–2026 period and that the principal change in the relationship is concentrated around the 2017–2018 transition. This reinforces the regime-specific evidence in Table 9 without changing the hypothesis decisions in Table 10.

9. Discussion

The central empirical finding is more nuanced than the common proposition that exchange-rate uncertainty automatically destabilizes the stock market. Over 2010–August 2026, rupee depreciation itself has a clearer relationship with equity outcomes than the GARCH-based uncertainty measure. This is economically plausible in an import-dependent economy because depreciation directly raises the domestic cost of energy, machinery and intermediate inputs and can intensify inflation and interest-rate expectations.

The significant EGARCH asymmetry nevertheless shows that the foreign-exchange market reacts differently to depreciation and appreciation. Depreciation shocks are

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associated with greater conditional FX volatility. Thus, even though the full-sample cross-market volatility coefficient is insignificant, adverse currency movements still create an asymmetric uncertainty process within the FX market.

The regime evidence also helps reconcile the present findings with earlier Pakistani studies that report stronger spillovers. The positive FXVOL coefficient in 2018–2019 indicates that uncertainty mattered more during a period of major exchange-rate adjustment. A constant-parameter model averages this effect together with periods in which the relationship is weak or negative.

These findings are consistent with the broader emerging-market literature showing that uncertainty effects depend on external vulnerability, global financial conditions and investor risk aversion [11,12]. They also align with recent SBP financial-stability analysis, which monitors exchange-rate volatility alongside other financial-market indicators [1].

10. Policy Implications

First, policymakers should distinguish orderly depreciation from disorderly volatility. The results suggest that the direction of the currency has direct equity-market consequences, while the uncertainty effect is regime dependent. Policy communication should therefore focus on credible macroeconomic adjustment and market functioning rather than defending a fixed numerical exchange-rate level.

Second, financial-stability surveillance should combine currency returns, currency volatility, equity volatility and drawdown measures. A composite approach is better suited to episodes in which market stress appears through several channels simultaneously.

Third, firms with substantial imported inputs or foreign-currency liabilities need stronger hedging and disclosure practices. More transparent reporting of net FX exposure would allow investors to differentiate naturally hedged exporters from firms whose margins are highly sensitive to rupee depreciation.

Finally, the significant 2018–2019 regime result suggests that exchange-rate uncertainty deserves particular attention during transitions in the exchange-rate framework or periods of rapid external adjustment. Macro-financial monitoring should therefore be state contingent rather than based solely on full-sample average relationships.

11. Limitations and Future Research

The main cross-market analysis is deliberately estimated at monthly frequency because the verified SBP exchange-rate series is monthly whereas the KSE-100 source is daily. This avoids creating pseudo-daily FX observations and preserves a reproducible common sample. A future extension using a verified daily interbank PKR/USD series could estimate synchronized DCC-GARCH or BEKK-GARCH models. The baseline specification also does not include a complete monthly set of inflation, policy-rate and oil-price controls. This matters because recent Pakistan evidence shows that oil-price and exchange-rate volatility can jointly shape equity outcomes [35]. Accordingly, the coefficients in this paper are interpreted as robust conditional associations within the available dataset, not as fully isolated structural effects. Sector-level analysis is another useful extension because exporters, banks and import-intensive firms have different currency exposures.

12. Conclusion

Using verified PKR/USD and KSE-100 data for January 2010–August 2026, this paper finds strong volatility clustering and a statistically significant asymmetric foreign-exchange volatility process. Rupee depreciation shocks raise FX volatility more strongly, and depreciation is associated with lower KSE-100 returns and higher composite financial instability. By contrast, the full-sample conditional exchange-rate-volatility measure does not significantly increase stock-market conditional volatility or the FMI. Monthly VAR tests also do not confirm bidirectional volatility causality.

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The results therefore refine rather than simply repeat the existing Pakistan literature. Exchange-rate uncertainty matters in particular regimes—most clearly in the 2018–2019 subsample—but its effect is not constant through time. For financial-stability policy, the implication is that the level, direction and uncertainty of the exchange rate should be monitored separately. For investors and firms, rupee depreciation remains a material source of equity and operating risk, while the volatility transmission channel becomes especially relevant during exchange-rate regime transitions and periods of external adjustment.

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