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Economic Policy Uncertainty, CPI Inflation and Nifty Financial Services Index Returns: An OLS-eGARCH-wavelet Analysis

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Abstract

This study seeks to analyse the impact of Economic Policy Uncertainty (EPU) and Consumer Price Index (CPI) Inflation on the returns of the Nifty Financial Services Index in the period of March 2015 to December 2024. EPU is believed to have an impact on FSI returns via real options, real options via information/investor sentiment channels and real options via credit demand compression, risk pricing effects and portfolio reallocation effects. Monetary policy expectations are a mechanism that passes on the inflation signal of CPI inflation, with higher inflation under the RBI's inflation targeting regime pushing up rate expectations, which subsequently squeezes net interest margins and increases equity discount rates. The monthly data for the period spanning major macroeconomic shocks including demonetization, the IL&FS crisis, the COVID 19 pandemic and RBI policy decisions were used for Ordinary Least Squares (OLS) estimates of mean return effects, Exponential Generalised Autoregressive Conditional Heteroskedasticity (EGARCH) estimation of asymmetric volatility dynamics and continuous wavelet coherence analysis. Mean FSI returns are difficult to explain by either EPU or CPI (R2 = 1.5- 1.8%) and neither variable has a direct influence on conditional variance in a linear model. Wavelet coherence analysis, however, shows that the co-movement of EPU-FSI increases in the medium to longer term (6-16 months) when policy crisis occurs. During inflationary periods, CPI-FSI co-movement focus is on a short to medium horizon (2-12 months). The results confirm that the time frequency dynamics is the primary mechanism of transmission and have clear implications for RBI forward guidance and horizon-specific portfolio management.

Keywords: CPI Inflation, Economic Policy Uncertainty, EGARCH Volatility, Financial Sector Returns, Nifty Financial Services Index, Wavelet Coherence.

Introduction

The Indian Nifty Financial Services Index, encompassing banking, Non-Banking Financial Companies (NBFCs), Insurance and Asset Management Services, represents over one-third of the market capitalisation of NSE and acts as the main mechanism for capital allocation towards long-term economic development. Comprising 20 stocks across four subsectors, it is highly susceptible to macroeconomic volatility and monetary policy shifts of the RBI, making it a barometer of macroeconomic stress in an emerging market. India constitutes a particularly pertinent context for this analysis for various reasons. It is world's fifth largest economy with a rapidly formalising financial system, FSI of India, includes banks, NBFCs, insurers and asset managers within a single index, examining the FSI is more informative than analysing the broad market index, as financial firms are disproportionately exposed to the precise policy channels, and the RBI's adoption of flexible inflation-targeting framework in 2016 introduced a structural break, enabling analysis under two distinct monetary regimes within the same study window.

Theoretically, EPU affects financial sector returns through three channels: (a) The real options channel, wherein elevated uncertainty increases the option value of waiting, compressing credit demand and raising equity risk premia, (b) The information channel, wherein ambiguous policy signals impair banks' ability to price credit and duration risk, and (c) The investor sentiment channel, wherein risk aversion triggers reallocation away from financial stocks (1–4). Economic policy uncertainty refers to the ambiguity surrounding future fiscal, monetary and regulatory policy commitments (5). Elevated EPU reduces investment, lowers GDP growth and increases employment volatility, as economic actors

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postpone irreversible decisions. This behaviour is explained by the real options framework (1, 2), wherein uncertainty raises the option value of waiting, magnifying capital cycle contraction and increasing the risk premium for financial intermediaries. At the firm level, EPU negatively affect capital expenditures and equity risk premia, while in debt markets, it raises loan pricing through elevated perceived default risk (3, 4, 6). CPI inflation transmits to FSI returns through monetary policy expectations: under the RBI's post 2016 flexible inflation targeting framework, rising inflation signals prospective rate hikes, compressing net interest margins and raising discount rates (7, 8). These transmissions are neither linear nor time-invariant; their strength and direction vary by investment horizon and crisis regime, which standard OLS and GARCH frameworks cannot capture (9, 10). Evidences from Indian financial markets indicate that scheduled macroeconomic announcements do not significantly affect mean equity returns, though volatility responses are marked. Abnormal mean return around CPI and WPI releases is statistically insignificant across sectoral indices and has further weakened since the implementation of the RBI's flexible inflation targeting regime in 2016 (7). India VIX shows no significant movement on CPI, WPI, IIP or GDP announcement days except during Monetary Policy Committee meetings, though positive mean return effects have been documented around unconventional RBI announcements, such as Long-Term Repo Operations during COVID-19 (11, 12). In the volatility dimension, EGARCH specifications outperform symmetric GARCH models in realising the asymmetric responses to negative return shocks for Indian banking stocks, and the financial sector has been identified as among the most EPU concentrated in amplifying the macro-financial transmission (13–15). At the global level, EPU has been shown to amplify Chinese stock market volatility, and EPU and oil price shocks have been found to drive cross-market volatility spillovers among G20 banking stocks (16, 17).

Wavelet coherence addresses weaknesses of time-domain models by uncovering horizon-contingent and crisis-contingent interdependencies. In the Indian context, EPU has been shown to strongly influence financial market volatility at medium scales (8–32 weeks), with coherence increasing during demonetization (2016–17) and the COVID-19 pandemic (2020) (9). Wavelet-based coherence exceeds that of linear time series models across EPU sectors and investment horizons, with significant implications for portfolio optimisation (10). In post-pandemic India, equity correlations have been shown to strengthen during stress events using VAR-DCC-GARCH and wavelet approaches, with comparable findings documented in the FinTech and ESG market (18, 19).

Research Gaps and Contributions

Research Gaps

Three research gaps remained unaddressed. No study has adopted the OLS regression, EGARCH and continuous wavelet coherence within the same analytical package to explore mean return, volatility and time-frequency relationship across a financial services index. Evidence on domestic macro-EPU interactions under the post-2016 RBI inflation targeting regime remains limited. Time frequency analysis of post-COVID-19 EPU spillovers into the financial services sector of India is absent from the existing literature (19).

Research Questions

This study addresses these gaps using monthly Nifty FSI return data from March 2015 to December 2024 (n=118, after transformation). Three research questions are examined:

RQ1: Do CPI inflation and EPU significantly predict mean FSI returns?

RQ2: Do they increase the conditional volatility of FSI returns?

RQ3: How do these relationships change with time and investment horizons?

Hypotheses development

H1 posits no significant mean return effect (7, 11).

H2 posits high volatility persistence with asymmetric leverage effects, but no direct linear variance transmission (13, 15).

H3 posits that EPU-FSI coherence strengthens at medium-to-long-term (6–16 months), during a policy crisis, while simultaneous evidence on mean, volatility and time frequency channels. Second, the complete post-inflation targeting period (March 2015 to 2024) is covered, encompassing four major macroeconomic CPI-FSI coherence concentrates at shorter to medium horizon (7, 9, 18).

Contributions

Three contributions follow. First, an integrated OLS-EGARCH-Wavelet framework is applied to a broad-based financial service index for the first time in the Indian context, providing shocks as natural experiments (7). Third, continuous wavelet coherence is established as the appropriate tool for multi-horizon analysis of macro-financial transmission, with findings offering actionable insights for RBI forward guidance, macroprudential policy designs and horizon-specific risk management (9).

Methodology

This study employs monthly data spanning March 2015 to December 2024 (n=118 observations after transformation) on India's NIFTY Financial Services Index returns (FSI_Return) sourced from NSE India, alongside lagged RBI repo rates (Repo_lag) from RBI announcements, lagged CPI inflation (CPI_lag) from MOSPI and Economic Policy Uncertainty (EPU) (20-23).

Data Analysis

Data were analysed using R statistical software for Windows, Version 4.5.0 (R Core Team, Vienna, Austria). Stationarity tests were conducted using the tseries package (v0.10-58). The estimation of EGARCH models was carried out with the package rugarch (v1.5-3; Ghalanos 2023). The WaveletComp package was used to perform wavelet coherence analysis. The diagnostic tests were carried out using the FinTS package. The Corrplot package (v0.94) was used to create correlation visualisation.

Results

Stationarity was established using Augmented Dickey-Fuller (ADF) tests, with the results for the original series and transformed series reported in Tables 1 and 2.

Table 1: ADF Table for Original Series

Variable	ADF_Stat	p value	Lag_Order	Stationary
FSI_Return	-5.1895	0.01	4	Yes (p<0.01)
CPI_lag	-1.1004	0.9189	4	No (p=0.92)
EPU	-3.3112	0.0728	4	No (p=0.07)
Repo_lag	-1.7517	0.6797	4	No (p=0.68)

Note: ADF = Augmented Dickey Fuller test; p = probability value; Lag_Order = number of lags selected by AIC; Yes/No = stationary/non-stationary at p < 0.05.

Table 2: ADF Table for Transformed Series

Variable	ADF_Stat	p value	Lag_Order	Stationary
CPI_final = Δlog(CPI_lag)	-6.2279	0.01	4	Yes (p<0.01)
EPU_final = Δlog(EPU+1)	-7.4562	0.01	4	Yes (p<0.01)

Note: ADF = Augmented Dickey-Fuller; p = probability value; AIC = Akaike Information Criterion.

Tables 1 and 2 report ADF test results for the original and transformed series, respectively. FSI_Return is stationary at levels (ADF = −5.190, $p < 0.01$, lag = 4), permitting direct use in regression. CPI_lag (ADF = −1.100, p = 0.919), EPU (ADF = −3.311, p = 0.073) and Repo_lag (ADF = −1.752, p = 0.680) are all non-stationary at the 5% level; Repo_lag was consequently excluded from all regression models. Table 2 confirms that first-differenced log transformations achieve stationarity: CPI_final = Δlog(CPI_lag) yields ADF = −6.228 ($p < 0.01$) and EPU_final = Δlog(EPU+1) yields ADF = −7.456 ($p < 0.01$), both with four lags selected by AIC. These transformed variables are used in all subsequent OLS and EGARCH estimations.

Ordinary least square regressions estimate mean effects using stationary series as specified in Equations [1, 2] report results in Tables 3-5 (9, 10).

$$\text{Model 1: } FSI\_Return\_t = \beta_0 + \beta_1 CPI\_final\_t + \beta_2 EPU\_final\_t + \varepsilon\_t \quad [1]$$

$$\text{Model 2: } FSI\_Return\_t = \beta_0 + \beta_1 CPI\_final\_t + \varepsilon\_t \quad [2]$$

Tables 3-5 presents OLS regression results for both models. In Model 1, the intercept is 0.0057 (SE = 0.0055, t = 1.038, p = 0.301), the CPI_final coefficient is 0.888 (SE = 0.690, t = 1.286, p = 0.201) and the EPU_final coefficient is −0.0065 (SE = 0.0113, t = −0.579, p = 0.564) neither predictor is statistically significant. Model 2 retains only CPI_final, with a coefficient of 0.924 (SE = 0.686, t = 1.347, p = 0.181), equally non-significant. Overall model fit is negligible: R^2 = 1.83% and Adjusted R^2

= 0.12% for Model 1; R^2 = 1.54% and Adjusted R^2 = 0.69% for Model 2. F-statistics are 1.07 (df = 2, 115; p = 0.347) and 1.82 (df = 1, 116; p = 0.181), respectively, confirming that neither model achieves joint significance. Residual diagnostics show no volatility clustering (ARCH-LM: Model 1 χ^2 = 14.40, p = 0.276; Model 2 χ^2 = 14.27, p = 0.284) and no serial autocorrelation (Ljung-Box Q (20): Model 1 p = 0.074; Model 2 p = 0.059), validating OLS assumptions. However, given the high kurtosis [9.307] and the potential for asymmetric volatility responses, EGARCH (1,1) models were subsequently estimated.

Table 3*:* OLS Regression Coefficient

	Model 1				Model 2			
Parameter	**Coefficient(β)**	**Std _Error**	**t_ value**	**p_ value**	**Coefficient(β)**	**Std_Error**	**t_value**	**p_value**
Intercept	0.0057	0.0055	1.0384	0.3012	0.0056	0.0055	1.0116	0.3138
CPI_final	0.888	0.6903	1.2864	0.2009	0.9236	0.6856	1.3473	0.1805
EPU_final	-0.0065	0.0113	0.5785	0.5641	----	----	----	----

Note: OLS = Ordinary Least Squares; FSI = Nifty Financial Services Index; CPI = Consumer Price Index; EPU = Economic Policy Uncertainty; SE = Standard Error.

Table 4: OLS Model Fit Statistics

Metric	Model_1	Model_2
R-squared	0.0183	0.0154
Adj R-squared	0.0012	0.0069
F-statistic	1.0697	1.8151
p-value (F)	0.3465	0.1805
Observations	118	118

Note: df = degrees of freedom; R^2 = coefficient of determination.

Table 5: OLS Residual Diagnostic Tests

Test	Model_1 Statistic	Model_1 p value	Model_2 Statistic	Model_2 p value
ARCH-LM test (χ^2, df=12)	χ^2=14.40	0.276	χ^2=14.27	0.284
Ljung-Box Q (20)	Q=29.76	0.074	Q=30.73	0.059

Note: ARCH = Autoregressive Conditional Heteroskedasticity; LM = Lagrange Multiplier; df = degrees of freedom. p > 0.05 indicates no volatility clustering (ARCH-LM) and no serial autocorrelation (Ljung-Box).

Table 6: Descriptive Statistics

Variable	N	Mean	SD	Min	Max	Skewness	Kurtosis
FSI_Return	118	0.0095	0.0508	-0.2646	0.1589	-1.337	9.3073
Repo_lag	118	5.7907	1.0579	4	7.75	-0.6491	2.141
CPI_lag	118	154.1814	21.8755	120.6	199.5	0.4053	1.9338
EPU	118	79.4312	32.8617	23.3528	193.1392	0.9653	3.6821

Note: FSI = Nifty Financial Services Index; CPI = Consumer Price Index; EPU = Economic Policy Uncertainty; SD = Standard Deviation; Min = Minimum; Max = Maximum; N = number of observations.

EGARCH (1,1) models capture asymmetric volatility as specified in Equation [3] with results reported in the following tables (24).

$$\log(\sigma^2{}_t) = \omega + \alpha_1|z_{t-1}| + \gamma_1 z_{t-1} + \beta_1\log(\sigma^2{}_{t-1}) + \lambda_1 vxreg1_t \qquad [3]$$

Where, $z_t = \varepsilon_t/\sigma_t$ denotes standardized residuals, γ_1 captures leverage effects (asymmetric response to negative shocks), β_1 measures volatility persistence and λ_1 is the coefficient of the external variance regressor (vxreg1).

Model 1 uses EPU_final as vxreg1; Model 2 uses CPI_final as vxreg1. Both models are estimated separately. Wavelet coherence analysis is used to analyse time-frequency relationships for stationary FSI_Return, CPI_final and EPU_final over different investment horizons.

Table 6 describe the descriptive statistics of the variables used in the current study over the study period (n=118). Mean return of FSI remained stable from 2015 to 2024 in India, even during major macroeconomic events, with volatility spiking during crisis periods. FSI returns averaged 0.0095 per month (SD = 0.0508), with a minimum of −0.2646 and a maximum of 0.1589, indicating that while average monthly returns were modestly positive, the distribution was subject to severe downside episodes. The negative skewness [−1.337] and high kurtosis [9.307] further validate fat-tailed, left-skewed return behavior characteristic of financial time series impacted by financial crises. The EPU index had a mean of 79.43 (SD = 32.86) and the range was 23.35 to 193.14, indicating the policy uncertainty during the sample period was quite large, with the highs coinciding with demonetization, COVID-19 and RBI tightening periods. CPI_lag had a mean of 154.18 (SD = 21.88) with moderate positive skewness [0.405]. Repo_lag had a mean of 5.79% (SD = 1.058) and negative skewness [−0.649], indicative of a declining rate environment over much of the sample. The Pearson correlation matrix and Variance Inflation Factors are presented in Tables 7 and 8 respectively. FSI returns show a weak positive correlation with CPI_lag (r = 0.049) and a moderate negative correlation with EPU (r = −0.251), suggesting that higher policy uncertainty is associated with lower financial sector returns, consistent with the investor sentiment channel. The Repo_lag is negatively correlated with both CPI_lag (r = −0.216) and FSI returns (r = −0.038), reflecting the RBI's tightening stance during inflationary periods. The highest inter-predictor correlation is between CPI_lag and EPU (r = 0.411), which is well below the conventional multicollinearity threshold of 0.80. VIF values for both transformed predictors (CPI_final and EPU_final) equal 1.008, confirming the complete absence of multicollinearity in the regression models.

Table 7: Pearson Correlation Matrix

Variable	FSI_Return	CPI_lag	EPU	Repo_lag
FSI_Return	1	0.0492	-0.2509	-0.0379
CPI_lag	0.0492	1	0.4113	-0.2155
EPU	-0.2509	0.4113	1	-0.0037
Repo_lag	-0.0379	-0.2155	-0.0037	1

Note: Pearson correlation coefficient; FSI = Nifty Financial Services Index; CPI = Consumer Price Index; EPU = Economic Policy Uncertainty.

Table 8: Variance Inflation Factor Model 1 CPI_final and EPU_final

Variable	VIF
CPI_final	1.008
EPU_final	1.008

Note: VIF applies to Model 1 only (2 predictors). VIF = Variance Inflation Factor.

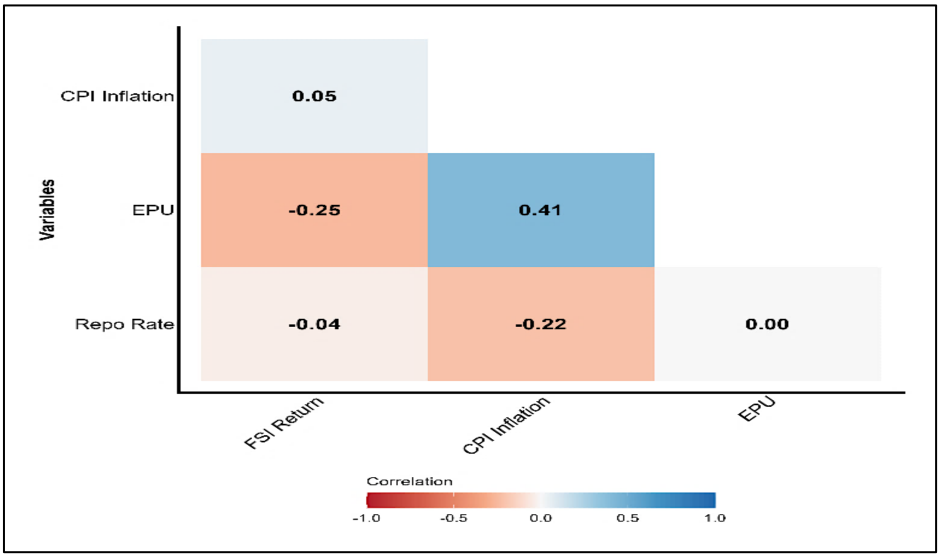

Figure 1: Correlation Matrix

Table 9: EGARCH (1,1) Mean Equation Estimation

Parameter	Model 1 (EPU as regressor)				Model 2 (CPI as regressor)			
	Estimate	Std_Error	t_value	p_value	Estimate	Std_Error	t_value	p_value
Mu μ (mean)	0.013	0.0047	2.687	0.007	0.011	0.004	2.8087	0.01

Note: μ = mean equation intercept; ** $p < 0.01$.

Figure 1 presents the Pearson correlation matrix for the four study variables. Visually confirming the results presented in Table 7. Variance Inflation factor is discussed in Table 8.

Table 9 presents EGARCH (1,1) estimation results as specified in Equation (3). In the mean equation, the intercept μ is significant in both models (Model 1: $\mu = 0.0126$, $p = 0.007$; Model 2: $\mu = 0.0113$, $p = 0.005$), confirming a positive baseline monthly return after controlling for volatility dynamics.

In the variance equation described in Table 10, the constant ω is non-significant in both models (Model 1: $\omega = -0.395$, $p = 0.282$; Model 2: $\omega = -0.490$, $p = 0.341$), indicating no unconditional shift in variance. The coefficient of conditional volatility on past shocks, α_1, is not significant in Model 1 (−0.135, $p = 0.153$) but marginally significant in Model 2 (−0.178, $p = 0.063$), indicating a weak short-run effect of past shocks on conditional volatility when CPI is the regressor on the variance. Volatility persistence β_1 is large and significant for both models (Model 1: 0.940, $p<0.001$; Model 2: 0.920, $p<0.001$), suggesting that volatility shocks are long-lived. In Model 1, a marginal leverage effect γ_1 is obtained (0.180, $p = 0.095$†), and in Model 2, a higher value is obtained (0.144, $p = 0.254$). This is consistent with the asymmetric downside risk amplification when EPU is the variance regressor. The external variance regressors are non-significant in both models (EPU_final: vxreg1 = 0.562, $p = 0.231$, CPI_final: vxreg1 = −4.700, $p = 0.704$). Although the CPI regressor is not statistically significant, its sign is directionally consistent with the RBI's active inflation-targeting policy that leads to a decrease in the surprise component of inflation, which also implies a decrease in conditional uncertainty, which would increase the financial market impact of the decrease in conditional uncertainty, but would not decrease it, given that the sign of the CPI regressor is negative. In fact, a positive CPI would imply an increase in the reaction of the market to a decrease in conditional uncertainty, which would be neutral with respect to the direction of the coefficient.

Table 10: EGARCH (1,1) Variance Equation Estimates

Parameter	Model 1 (EPU)				Model 2 (CPI)			
	Estimate	Std_Error	t_value	p_value	Estimate	Std_Error	t_value	p_value
ω (omega)	-0.395	0.3667	-1.076	0.282	-0.49	0.514	-0.9529	0.34
α_1 (ARCH effect)	-0.135	0.0942	-1.43	0.153	-0.18	0.096	-1.8565	0.06
β_1 (persistence)	0.94	0.0595	15.78	0	0.92	0.084	10.953	0
γ_1 (leverage)	0.18	0.1076	1.668	0.095	0.144	0.126	1.141	0.25
vxreg1 (EPU/CPI)	0.562	0.4683	1.199	0.231	-4.7	12.36	-0.3802	0.7
shape (ν)	6.429	2.7117	2.371	0.018	5.895	2.228	2.6457	0.01

Note: ω = variance constant; α_1 = ARCH effect; β_1 = volatility persistence; γ_1 = leverage effect; ν = shape parameter; vxreg1 = external variance regressor.

Table 11: EGARCH (1,1) Model Fit and Diagnostic Tests

Metric	Model 1 Value	Model 2 Value
Log-Likelihood	200.009	199.37
AIC (Akaike)	-3.271	-3.261
BIC (Bayesian)	-3.107	-3.096
Ljung-Box p (standardised resid)	0.464	0.428
ARCH-LM p (standardised resid)	0.998	1

Note: AIC = Akaike Information Criterion; BIC = Bayesian Information Criterion. Ljung-Box $p > 0.05$ indicates no serial autocorrelation. ARCH-LM $p > 0.05$ confirms no remaining volatility clustering in standardised residuals.

Model fit metrics are explained in the Table 11 are comparable across both specifications (Model 1: Log-Likelihood = 200.009, AIC = −3.271, BIC = −3.107; Model 2: Log-Likelihood = 199.370, AIC = −3.261, BIC = -3.096), with a marginally better fit in Model 1. Shape parameters are significant in both models (Model 1: ν = 6.429, p = 0.018; Model 2: ν = 5.895, p = 0.008), confirming fat-tailed conditional distributions. Post-estimation diagnostics confirm full model adequacy: Ljung-Box Q (20) detects no serial autocorrelation in standardised residuals (Model 1: p = 0.464; Model 2: p = 0.428) and ARCH-LM tests detect no remaining volatility clustering (both p > 0.99) (25). A marginal leverage effect is confirmed in Model 1 (γ_1 = 0.180, p = 0.095), while Model 2 shows no significant leverage effect (γ_1 = 0.144, p = 0.254). The diagnostic tests also showed the adequacy of the model as supported by Ljung-Box and post-EGARCH ARCH-LM tests at p-values greater than 0.20 and 0.05, respectively.

The results of the wavelet coherence analysis showed the existence of regime-dependent co-movements between CPI and FSI during the COVID-19 period and the inflationary pressures in 2022-2023 at short- to medium-term horizons. On the other hand, the co-movements between EPU and FSI were found to have persisted during the demonetization, IL&FS and COVID-19 periods at medium-to-long-term horizons (6–16 months). Figure 2A presents continuous wavelet coherence plots between FSI returns and CPI Inflation while Figure 2B presents continuous wavelet coherence plots between FSI returns and EPU. In Figure 2, The results of the wavelet coherence analysis showed the existence of regime-dependent co-movements between CPI and FSI during the COVID-19 period and the inflationary pressures in 2022-2023 at short- to medium-term horizons. On the other hand, the co-movements between EPU and FSI were found to have persisted during the demonetization, IL&FS and COVID-19 periods at medium-to-long-term horizons (6–16 months).

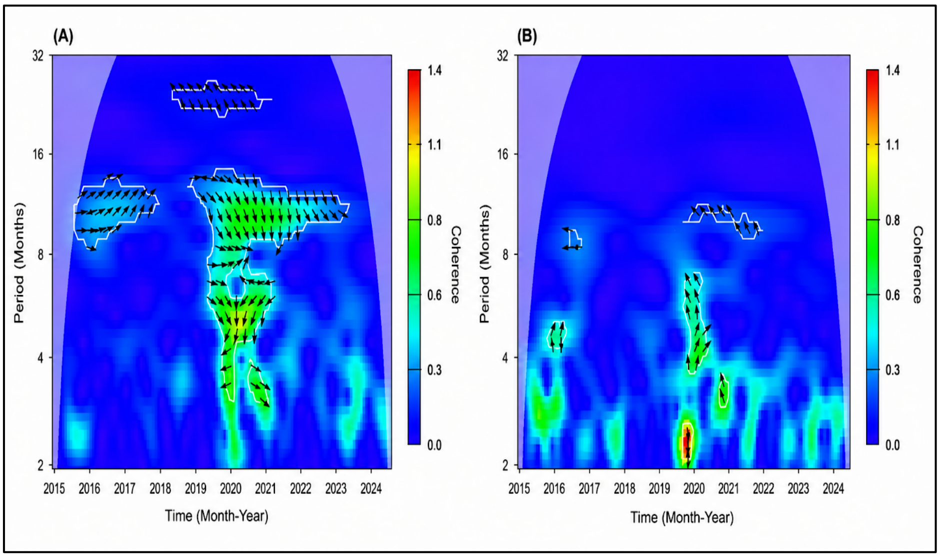

Figure 2: Wavelet coherence: FSI_Return. (A) FSI Return vs CPI, (B) FSI Return vs EPU

Overall, the results suggest that macroeconomic variables have little impact on FSI's mean returns, but their effects are mainly channeled through time-frequency channels, as revealed by wavelet coherence analysis. These results have implications for investor hedging strategies and the RBI's communication strategies during periods of high uncertainty.

Robustness Checks

To validate the results obtained in the previous section, robustness checks were undertaken by using different specifications of volatility and different compositions of the sample period. The symmetric GARCH (1,1) and threshold models of TGARCH (1,1) produced similar results. Volatility persistence remained high, and neither EPU nor CPI became a significant variance driver across alternative specifications. Specifically, GARCH (1,1) estimates yielded volatility persistence coefficients of $\beta \approx$ [0.93-0.96] and TGARCH (1,1) confirmed asymmetric leverage effects consistent with EGARCH findings, with neither EPU nor CPI achieving significance as external variance drivers ($p > 0.10$ across all specifications). The results obtained from analysing the pre- and post-COVID-19 periods were similar. However, the effects were stronger during the crisis periods. The use of different measures of inflation, namely year-over-year CPI inflation and raw EPU indices, produced similar results. The results obtained from using winsorized returns were similar and retained the same significance levels as those obtained in the previous section. All diagnostic tests were satisfactory.

Discussion

The Financial Services Index's mean returns over 2015-2024 are robust, despite significant macroeconomic shocks like the 2016 demonetization, 2018 IL&FS-NBFC crisis, the COVID-19 pandemic and the 2022-2023 RBI policy tightening, increasing the repo rate from 4% to 6.5% (8, 26). Descriptive statistics of FSI returns show negative skewness of -1.337 and high kurtosis of 9.307, suggesting crisis-driven fat tails, unlike CPI inflation, whose high variance with low correlations between variables (maximum $|r| = 0.411$) and variance inflation factor of 1.008 suggest the existence of independent transmission channels. The stationarity of FSI returns ($p = 0.01$) and transformed macro variables like ΔlogCPI, Δlog(EPU+1), was confirmed using ADF tests, justifying the exclusion of non-stationary variables like repo rates in the regression equation (27).

Ordinary least squares regression results show negligible conditional mean effects of macroeconomic variables like CPI and EPU, with R^2 ranging from 1.5-1.8%, CPI p-values ranging from 0.181-0.201 and EPU $p = 0.564$, suggesting macroeconomic shocks are responsible for inducing volatility in FSI returns rather than affecting its means, a finding consistent with the Prior evidence from Indian Equity markets showing statistically insignificant mean return responses to scheduled macroeconomic announcements, with the effect further weakening under the inflation targeting framework of RBI (7, 11). Strong volatility persistence was confirmed through EGARCH (1,1) estimation (Model 1: $\beta_1 = 0.940$, $p < 0.001$) (13, 24). This increased persistence is consistent with recent post-pandemic evidence from Indian financial markets, where volatility shocks show slow mean reversion in GARCH family estimation (18). The non-significant external variance regressors (EPU: $p = 0.230$; CPI: $p = 0.704$) suggest that transmission does not operate through a direct linear variance channel. Recent cross-market evidence similarly confirms that EPU transmits to the financial sector returns through indirect channels rather than a direct variance mechanism in emerging market contexts (15, 16). Both models show similarly high volatility persistence ($\beta \approx 0.920–0.940$), consistent with the well-communicated and sequential RBI rate adjustments from 4% to 6.5% (8). A marginal leverage effect was confirmed in Model 1 ($\gamma_1 = 0.180$, $p = 0.095$), indicating that positive shocks generate slightly larger volatility responses than negative shocks of equivalent magnitude in the FSI during elevated policy uncertainty periods. Model adequacy was validated by diagnostics such as ARCH-LM $p > 0.05$ and Ljung-Box $p > 0.20$ (25, 28). The wavelet coherence further establishes that at certain scales or regimes, such as in the case of COVID-19 or inflationary situations, CPI-FSI has stronger linkages at shorter to medium-term scales (2-12 months), whereas EPU-FSI has stronger linkages at longer scales (6-16 months), which hold across policy crises (29). This horizon-dependent structure validates wavelet-based evidence from Indian sectoral indices showing EPU transmission concentrating at medium scale during policy stress, and cross-country evidence confirming EPU-financial sector coherence dominates at medium to long term horizons in emerging markets (9, 0). However, in later years, i.e., post-2023, the effect diminishes, consistent with post-crisis normalisation as RBI policy uncertainty receded following rate stabilisation.

These findings collectively establish that the dominant transmission channel from macroeconomic variables to financial sector returns operates through time-frequency dynamics, not through linear mean or variance mechanisms. Standard OLS or GARCH-based risk models will systematically underestimate macro-financial linkages during crisis periods. Investors should incorporate wavelet-based horizon-specific coherence measures into portfolio risk frameworks. Forward guidance and a transparent communication strategy of the RBI have been confirmed as critical tools for reducing uncertainty-driven volatility. Transparent central bank communication under inflation targeting has been shown to materially reduce the uncertainty premium in Indian financial markets in the post-2016 period (8, 30).

The policy recommendations include calibrated RBI communication to mitigate EPU spillovers, targeted liquidity provision in times of crises and macroprudential policies implemented at specified uncertainty levels (8, 31). Further research should be conducted to extend the proposed OLS-EGARCH-Wavelet approach to accommodate global variables, sectoral analysis, non-linear modelling, or ESG channels in EM countries (18, 19).

Conclusion

This research has shown that the Indian Financial Services Index (FSI) has recorded stable mean returns from 2015 to 2024, even with considerable macroeconomic shocks, including the 2016 demonetization, 2018 IL&FS-NBFC crisis, COVID-19 pandemic and 2022–2023 RBI tightening. Descriptive statistics have also shown that FSI returns exhibit fat-tailed distributions (skewness = -1.337, kurtosis = 9.307), with low multicollinearity between CPI and EPU (maximum |r| = 0.411, VIF = 1.008). The stationarity of FSI returns, as well as the transformation of macroeconomic variables, provide a robust framework for analysis, with OLS showing that macroeconomic variables have a negligible mean effect on FSI returns (R^2 = 1.5-1.8%, p = 0.181-0.201 for CPI, p = 0.564 for EPU).

The EGARCH (1,1) model finds strong intrinsic volatility persistence in FSI returns ($\beta_1 \approx 0.940$, $p < 0.001$), with neither EPU nor CPI directly driving conditional variance (EPU: p = 0.230; CPI: p = 0.704), indicating that macroeconomic uncertainty transmits to financial sector volatility through indirect channels rather than a direct linear variance mechanism; a marginal leverage effect is confirmed in Model 1 ($\gamma_1 = 0.180$, $p = 0.095$). Wavelet coherence also finds evidence of distinct regime-dependent dynamics, including transient CPI-FSI co-movements at short-to-medium horizons (2–12 months) during inflationary episodes and persistent EPU-FSI co-movements at medium-to-long horizons (6–16 months) across policy crises. This study makes three contributions to literature. First, it applies an integrated OLS-EGARCH-Wavelet framework to the Nifty Financial Services Index for the first time in the Indian context, simultaneously capturing mean return, conditional volatility and time-frequency transmission channels within a single analytical package. Second, it covers the complete post-inflation-targeting period from March 2015 to December 2024, encompassing four major macroeconomic shocks: demonetization, the IL&FS crisis, the COVID-19 pandemic and the 2022–2023 RBI tightening cycle as natural experiments for testing macro-financial linkages under two distinct monetary regimes. Third, it establishes continuous wavelet coherence as the appropriate tool for multi-horizon analysis of macro-financial transmission in emerging market settings, demonstrating that time-frequency dynamics rather than linear mean or variance channels constitute the dominant mechanism through which EPU and CPI propagate to financial sector returns. The policy implications include RBI forward guidance to mitigate EPU effects, implementing macroprudential policy at predefined levels of uncertainty and hedging strategies that match investor horizons.

Limitations include the impact of monthly data on intra-monthly dynamics, excluding repo rate due to non-stationarity, using only domestic EPU while excluding global effects and using sectoral data that masks bank/NBFC heterogeneity effects.

Future research should include using high-frequency data, global uncertainty indices, sectoral data and ESG factors using a TVP-VAR or quant models, including quant EGARCH models. FSI resilience underscores policy communication as the key stability anchor in emerging markets.

Abbreviations

ADF: Augmented Dickey-Fuller, ARCH: Autoregressive Conditional Heteroskedasticity, CPI: Consumer Price Index, DCC: Dynamic Conditional Correlation, EGARCH: Exponential Generalized Autoregressive Conditional Heteroskedasticity, EPU: Economic Policy Uncertainty, ESG: Environmental Social and Governance, FSI: Nifty Financial Services Index, GARCH: Generalized Autoregressive Conditional Heteroskedasticity, OLS: Ordinary Least Squares.

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Author Contributions

All authors contributed to the manuscript. Maneesha MK: Introduction, Literature review, Data Analysis, Discussion of Results, References, Saravanabhavan N: Data Analysis, Discussion of Results, Manuscript Verification. Both the authors read the full manuscript and approved.

Conflict of Interest

The authors declare that there is no conflict of interest.

Data Availability

All data used in the study are publicly available from the following sources: Nifty financial service index return data from NSE India, Consumer Price index data from the Ministry of Statistics and Programme Implementation, RBI Repo rate data and India Economic Policy. The compiled data can be acquired from the corresponding author on a reasonable request.

Declaration of Artificial Intelligence (AI) Assistance

Authors have used AI assistance for grammar checking and language articulation. The authors take full responsibility for the content's originality, interpretation and accuracy.

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