



Global Uncertainty Spillovers: The Impact of U.S. Economic Policy Uncertainty on Emerging Market Volatility

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MSc in Finance

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May 2026

Abstract

This study examines Economic Policy Uncertainty (EPU) spillovers on equity volatility in the U.S., India, Brazil, Canada, and Japan using an augmented HAR-X framework. Findings identify the U.S. as a global uncertainty hub, and U.S. EPU shocks affect emerging markets more significantly than domestic factors. We reveal a state-dependent mechanism where EPU's predictive power intensifies during high-market-stress regimes. While spillovers are pervasive, emerging economies show higher vulnerability than developed counterparts. Rolling-window coefficient analysis uncovers significant time-varying dynamics, while out-of-sample tests confirm superior forecasting accuracy. These results highlight the need for emerging market policymakers to prioritize U.S. policy narratives in risk-management.

Keywords: Economic Policy Uncertainty, Realized Volatility, HAR-X Model, Spillover Effects, Emerging Markets, Financial Stability.

Supervisor: Tobias Sichert, Assistant Professor, Department of Finance, Stockholm School of Economics.

Acknowledgements: I would like to thank my supervisor Tobias Sichert for his guidance during the writing of this thesis.

Contents

1	Introduction	3
1.1	Motivation and Economic Context	3
1.2	Research Objectives and Main Results	3
2	Literature Review and Stylized Facts	5
2.1	Theoretical Foundations of Uncertainty	5
2.2	The Evolution of the HAR Framework	6
2.3	EPU and the Global Financial Cycle	6
2.4	International Transmission of Uncertainty	7
3	Methodology and Data	9
3.1	Data Collection and Preprocessing	9
3.2	Realized Volatility Estimation	10
3.3	The HAR-X Model Framework	10
3.4	Descriptive Statistics	10
4	Empirical Results and Analysis	13
4.1	Main Regression Results	13
4.1.1	Comparative Efficiency of Volatility Estimators	13
4.1.2	The Incremental Role of VIX and EPU	13
4.1.3	Multicollinearity Analysis	14
4.2	Volatility Spillover Analysis: Impact of U.S. Economic Policy Uncertainty . . .	15
4.2.1	Spillover Regression Results	16
4.2.2	Multicollinearity Analysis for Spillover Models	17
4.3	Regime-Dependent Analysis: Market Stress and EPU Sensitivity	17
4.3.1	Sub-sample Evidence across U.S., India, and Brazil	18
4.3.2	Distinct Dynamics in Emerging Markets	19
4.3.3	State-Dependent Sensitivity and Interaction Effects	19
4.3.4	State-Dependency in U.S.-led Uncertainty Spillovers	20
4.4	Rolling Window Coefficient Analysis: Time-Varying Dynamics	20
4.4.1	Analysis of Local EPU Impact Dynamics	21
4.4.2	Dynamic Spillovers from U.S. Policy Uncertainty	23
4.4.3	Summary of Dynamic Findings	23
4.5	Out-of-Sample Predictive Performance	23
4.5.1	Local Predictive Power	25
4.5.2	The Superiority of Spillover Spillovers	25
4.5.3	Summary of OOS Findings	26

4.6	Supplementary Analysis: Developed Markets Comparison	26
5	Discussion	28
5.1	The “Uncertainty Multiplier”: Reconciling VIX and EPU	28
5.2	The Dominance of U.S. Spillovers	28
5.3	Predictive Utility: Beyond Point Forecasts	29
5.4	Policy Recommendations	29
6	Conclusion	30
6.1	Summary of Findings	30
6.2	Contributions to Literature	30
6.3	Limitations	31
6.4	Directions for Future Research	31
6.5	Final Remarks	31
	References	32
	Appendix: Statement on the Use of Artificial Intelligence	33

1 Introduction

The globalization of financial markets has fundamentally reshaped how systemic risks spread across borders. In today's world, the integration of capital markets means that localized policy adjustments by major economies are no longer confined to specific regions. Instead, they spread through complex financial channels, influencing global asset prices and volatility mechanisms. This study explores the intersection of macroeconomic policy risk and financial econometrics, focusing on how economic policy uncertainty (EPU) can be a major catalyst for market turmoil. By bridging the gap between domestic policy shocks and the spillover effects of international volatility, this study provides a comprehensive analysis of the interconnectedness between the world's leading economies and major emerging financial centers.

1.1 Motivation and Economic Context

Following the 2008 global financial crisis and the subsequent COVID-19 pandemic, the concept of uncertainty has transitioned from a fringe issue to a core pillar of financial econometrics. EPU, defined as the uncertainty surrounding future government actions, fiscal adjustments, and monetary interventions, has been identified as a major driver of market volatility. While traditional asset pricing models focus on realized shocks, modern volatility research attempts to capture the shadow cast by unobserved policy trajectories.

The core economic issue explored in this study is the asymmetry of uncertainty transmission. Specifically, we examine whether emerging markets such as India and Brazil can manage their volatility, or whether their financial stability is fundamentally dependent on the U.S. political environment. In an era of "Polycrisis" dominated by trade tensions and interest rate shifts, understanding the lead-lag relationship between U.S. policy uncertainty and global equity risk is crucial for macroprudential regulation and portfolio optimization.

1.2 Research Objectives and Main Results

This study aims to answer four critical questions regarding the role of policy uncertainty in financial markets: (1) Does domestic EPU provide incremental predictive power for future realized volatility beyond market-based indicators? (2) Does the impact of EPU exhibit a state-dependent or "threshold" effect during periods of market distress? (3) To what extent does U.S. policy uncertainty spill over to emerging markets, and is this spillover more potent than domestic signals? (4) How do the sensitivities to domestic and international policy uncertainty evolve dynamically over historical and crisis-ridden horizons?

The main results are summarized as follows. First, our findings show the incremental predictive value of domestic EPU. Domestic EPU serves as a statistically significant predictor of future realized volatility. Even after controlling for the high persistence of volatility (HAR

components) and forward-looking market fear (VIX), EPU provides additional explanatory power.

Furthermore, the transmission of EPU shocks appears to be state-dependent, particularly within the U.S. market. EPU becomes a statistically significant driver of volatility ($p < 0.01$) only when the VIX breaches the 75th percentile threshold (22.73), confirming that policy shocks amplify existing market fear.

In a global context, the data reveals a U.S.-led spillover dominance that reshapes the risk landscape of emerging economies. For emerging markets like India and Brazil, domestic EPU signals are often overshadowed by exogenous shocks from the U.S. The U.S. policy uncertainty has a more consistent and robust influence on the Nifty 50 and Ibovespa than local policy narratives, supporting the Global Financial Cycle theory.

Finally, the dynamic sensitivity of these markets shows a pervasive decoupling failure during periods of heightened instability. Rolling window analysis reveals that emerging markets act as “risk resonators.” During global crises (2008 and 2020), the sensitivity of India and Brazil to US policy shocks often mirrors or exceeds that of the U.S. domestic market, indicating a failure of international decoupling.

2 Literature Review and Stylized Facts

This section provides a theoretical and empirical framework for our study of the cross-border impacts of U.S. policy uncertainty on emerging market volatility. First, we review the theoretical foundations of uncertainty, particularly the “real options” and “risk premium” channels that explain how policy ambiguity disrupts market stability. Then, we turn to a methodological framework, explaining how heterogeneous autoregressive (HAR) models and their extended model (HAR-X) effectively capture the multi-cycle nature of financial volatility. Furthermore, we place our research within the context of global financial cycles, examining the key role of the EPU index as a quantifiable driver of international capital flows. Finally, we integrated existing literature on the international transmission of uncertainty, highlighting the U.S. as a global center of uncertainty and the resulting sensitivity gaps in emerging economies such as India and Brazil. These elements collectively form a comprehensive benchmark for our empirical analysis of volatility spillover effects.

2.1 Theoretical Foundations of Uncertainty

To understand why policy uncertainty rattles stock markets, we can look at two primary economic explanations: the “real options” effect and the “risk premium” channel. At its core, uncertainty acts as a signal for businesses to pause. As Bernanke (1983) explains, most business decisions such as building a new factory or hiring a large team, are hard to reverse and involve high costs. When the government’s next move is unclear, the smartest move for a company is often to “wait and see.” This delay in spending and investment ripples through the economy, weakening demand and causing market ripples as investors try to guess what future profits will actually look like.

From an investor’s perspective, this uncertainty also changes how they price stocks. When investors are unsure about future taxes or interest rates, they become more cautious and demand a higher return for taking the risk of holding shares. This shift naturally pushes stock prices down. Pástor and Veronesi (2013) point out that policy uncertainty is especially tricky because it is a “systemic risk.” Investors cannot easily hide from it by diversifying their portfolios. This forced shift in market expectations is a major reason why we see sudden spikes in volatility.

Furthermore, Pástor and Veronesi (2013) introduce the interesting idea of government “put protection.” In stable times, markets often feel a sense of security, believing the government will step in if things go wrong. However, when political uncertainty rises, this invisible safety net starts to fray, making the entire market more fragile. Importantly for our study, they found that this effect is much stronger when the economy is already weak. This helps explain the “sensitivity gap” we observe: emerging markets like India and Brazil, which often have more fragile economic foundations than the U.S., tend to react much more violently to policy shocks from abroad.

Finally, we must consider the broader economic environment. Bloom (2009) describes uncertainty as a major “shifter” of the economy. They argue that uncertainty shocks act like a brake on economic activity, causing production and employment to drop quickly while recovery stays slow. This creates a stressful cycle: a slowing economy makes investors more anxious, which in turn fuels even more market volatility. In today’s interconnected world, these shocks do not stop at the border. Through international trade and global finance, uncertainty in a major hub like the U.S. has become a global risk factor, triggering volatility shifts in markets across the world.

2.2 The Evolution of the HAR Framework

To effectively capture the most prominent stylized facts of financial volatility, most notably the phenomenon of volatility clustering and the presence of long-memory, Corsi (2009) introduced the HAR model. Unlike traditional GARCH-family models that can be mathematically complex and computationally demanding, the HAR model is celebrated for its parsimonious structure and its remarkable ability to replicate the persistence found in realized volatility.

The core success of the HAR framework lies in its theoretical alignment with the Heterogeneous Market Hypothesis. It is designed to mimic the distinct behaviors of various market participants who operate across different time horizons. In this setup, the market is composed of a diverse array of agents, including high-frequency intraday traders (daily component), institutional investors who rebalance portfolios on a short-term basis (weekly component), and long-term fund managers who focus on monthly trends (monthly component). By modeling realized volatility as a sum of these additive cascades, the HAR model accounts for the fact that short-term traders are highly sensitive to long-term volatility trends, whereas long-term investors are generally less affected by daily market noise.

Building upon this robust autoregressive foundation, our study utilizes the HAR-X extension. This augmented framework allows for the integration of exogenous variables directly into the linear structure of the model. By incorporating forward-looking market indicators like the VIX and macro-level uncertainty measures such as the EPU, the HAR-X model moves beyond historical extrapolation. Instead, it creates a more holistic predictive structure where the autoregressive persistence of volatility is adjusted by external shocks and policy signals. This integration is crucial for enhancing predictive accuracy, as it enables the model to account for sudden shifts in market sentiment and global policy environments that traditional volatility models might otherwise overlook.

2.3 EPU and the Global Financial Cycle

The development of the news-based EPU index by Baker *et al.* (2016) has revolutionized the empirical study of policy-related risk. By utilizing standardized frequency counts of newspaper articles containing keywords related to economy, policy, and uncertainty, this methodology pro-

vides a continuous and quantifiable measure of a previously latent variable. Unlike traditional proxy variables, the EPU index captures the public’s perception of policy shifts in real-time, allowing researchers to track how expectations regarding fiscal, monetary, and regulatory actions influence market stability.

In an increasingly integrated global economy, recent scholarship has shifted its focus toward the international transmission of these uncertainty shocks. This line of inquiry is deeply connected to the concept of the “Global Financial Cycle” as proposed by Rey (2013). Rey argues that global capital flows, credit growth, and asset prices are not only driven by domestic conditions but are significantly dictated by a common global factor, primarily driven by U.S. monetary policy and the fluctuations in global risk appetite. This cycle suggests that emerging markets often face a dilemma where their financial conditions are tied to the decisions and stability of the world’s leading economy, regardless of their own exchange rate regimes.

Our study seeks to extend this framework by isolating a specific driver of this cycle: U.S. policy uncertainty. It is important to distinguish between actual policy changes such as an adjustment in the federal funds rate and the uncertainty surrounding the future direction of such policies. Even in the absence of an immediate policy shift, the mere ambiguity of the U.S. political and regulatory landscape can act as a potent shock to global risk sentiment. By focusing on emerging giants such as Brazil and India, we investigate whether U.S. EPU serves as an independent catalyst for the Global Financial Cycle, potentially having a stronger influence on their market volatility than their own domestic policy environments.

2.4 International Transmission of Uncertainty

The theoretical foundation of uncertainty contagion is deeply rooted in the literature regarding cross-border spillovers. A crucial contribution in this domain is the work of Klößner and Sekkel (2014), who provided some of the first empirical evidence on the international transmission of policy uncertainty using a VAR-based connectedness framework. They analyzed the EPU indices of six major developed economies, and demonstrated that policy uncertainty is far from a localized phenomenon. Rather, it exhibits significant transborder dynamics.

Crucially, Klößner and Sekkel (2014) identified a distinct asymmetry in the global uncertainty landscape. Their results categorized the U.S. and the U.K. as the primary net transmitters of uncertainty shocks, while other developed nations predominantly acted as net receivers. This finding lends strong academic support to our characterization of the U.S. as a “Global Uncertainty Center.” Furthermore, they observed that while spillovers typically account for slightly more than one-fourth of the total uncertainty dynamics, this share surged to over 50% during the 2008 global financial crisis.

This time-varying and crisis-contingent nature of spillovers suggests that the interconnect- edness of global markets is not static but intensifies during periods of high macro-financial stress. By building upon this framework, our study extends the scope of analysis to emerging

giants such as India and Brazil. We investigate whether these economies, which are already vulnerable to idiosyncratic volatility, experience a similar doubling of sensitivity when U.S. policy uncertainty fluctuates, thereby bridging the gap between developed-market spillover theory and emerging-market empirical realities.

A stylized fact observed in our data is the “sensitivity gap”: while the U.S. market is often resilient to minor domestic policy shifts, the Nifty 50 (India) and Ibovespa (Brazil) often overreact to headlines originating from Washington D.C., a phenomenon we analyzed through spillover models and rolling regressions in this study.

3 Methodology and Data

This section outlines the empirical framework and the dataset employed to investigate the predictive link between economic policy uncertainty and financial volatility. We begin by detailing the multi-source data collection process, which includes market prices, forward-looking sentiment indices, and news-based policy uncertainty measures across five distinct economies. Following this, we define the Garman-Klass estimator used to derive robust realized volatility measures. The core of our methodology centers on an HAR-X framework, designed to capture volatility persistence across different time horizons while accounting for exogenous macro-policy shocks. Finally, we provide a preliminary analysis of the data through descriptive statistics to identify the fundamental characteristics of the variables under study.

3.1 Data Collection and Preprocessing

The empirical analysis focuses on five major economies representing both developed and emerging markets: the U.S., Canada, Japan, India, and Brazil. The specific start dates of the dataset vary based on the availability of market volatility and policy uncertainty indices, particularly for the emerging markets and historical developed market records.

Market price data, including daily Open, High, Low, and Close (OHLC) prices, were retrieved from Yahoo Finance. Specifically, we utilize the S&P 500 (^GSPC) for the U.S., the S&P/TSX Composite Index (^GSPTSE) for Canada, the Nikkei 225 (^N225) for Japan, Nifty 50 (^NSEI) for India, and Ibovespa (^BVSP) for Brazil. The OHLC data coverage is as follows: the U.S. (1927-12-30 to 2026-05-08), Canada (1979-06-29 to 2026-05-08), Japan (1965-01-05 to 2026-05-08), India (2007-09-17 to 2026-05-08), and Brazil (1993-04-27 to 2026-05-08).

To capture market sentiment and forward-looking expectations of risk for our primary analysis targets, we obtain the corresponding Volatility Indices (VIX): the CBOE VIX for the U.S., India VIX (^INDIAVIX) for India, and the CBOE MSCI Brazil Volatility Index (^VXEWZ) for Brazil. The VIX data for the U.S. covers 1990-01-02 to 2026-05-08; for India it is 2008-03-03 to 2026-05-08; for Brazil it is 2023-06-26 to 2026-05-08.

For macroeconomic uncertainty measures, Economic Policy Uncertainty (EPU) data are sourced from the database developed by Baker *et al.* (2016). While we utilize the native daily EPU index for the U.S. starting from 1985, EPU indices for other jurisdictions are primarily published at a monthly frequency. To ensure synchronization with daily financial market data, we apply a forward-filling interpolation method to generate daily time series for Canada, Japan, India, and Brazil. After interpolation, the EPU data coverage includes: the U.S. (1900-01-01 to 2026-05-06), Canada (1985-01-01 to 2026-04-30), Japan (1987-01-01 to 2026-04-30), India (2003-01-01 to 2026-04-30), and Brazil (1991-01-01 to 2026-04-30). This standardized preprocessing approach facilitates robust time-series estimation and cross-country spillover analysis.

3.2 Realized Volatility Estimation

To provide a comprehensive analysis of market volatility, we employ two proxies for daily realized volatility (RV). First, as a baseline for our initial analysis in Model 1, we calculate the simple daily squared log-return (SRV), defined as:

$$SRV_t = \left(\ln \frac{C_t}{C_{t-1}} \right)^2 \quad (1)$$

where C_t and C_{t-1} denote the closing prices on day t and $t - 1$, respectively.

Furthermore, to estimate daily RV without the requirement of high-frequency intraday data, we employ the Garman and Klass (1980) volatility estimator (GK_RV). The GK estimator is significantly more efficient than simple squared returns as it incorporates intraday price range information (High and Low) alongside opening and closing prices. The estimator is defined as:

$$GK_RV_t = 0.5 \left(\ln \frac{H_t}{L_t} \right)^2 - (2 \ln 2 - 1) \left(\ln \frac{C_t}{O_t} \right)^2 \quad (2)$$

where O_t, H_t, L_t , and C_t represent the Open, High, Low, and Close prices on day t , respectively.

By utilizing both SRV and GK_RV , we can evaluate whether the inclusion of intraday price dynamics significantly improves the predictive power of our uncertainty-augmented HAR models.

3.3 The HAR-X Model Framework

To capture the heterogeneous nature of market participants and the potential impact of exogenous policy shocks, we extend the HAR model proposed by Corsi (2009). By incorporating VIX and EPU as exogenous regressors, our HAR-X model is specified as:

$$RV_{t+1} = \beta_0 + \beta_d RV_t + \beta_w RV_{t,w} + \beta_m RV_{t,m} + \gamma \ln(VIX_t) + \delta \ln(EPU_t) + \varepsilon_{t+1} \quad (3)$$

where RV_t , $RV_{t,w}$, and $RV_{t,m}$ represent the daily, weekly (5-day average), and monthly (21-day average) components of realized volatility, respectively. These components reflect the different investment horizons of market participants. The terms $\ln(VIX_t)$ and $\ln(EPU_t)$ denote the logarithmic transformations of the market volatility index and the economic policy uncertainty index.

3.4 Descriptive Statistics

Table 1 reports the summary statistics for the key variables across the three mainly analyzed markets: the U.S., India, and Brazil. The dataset includes realized volatility proxies (GK_RV , Ret_Sq), market-based implied volatility (VIX), and economic policy uncertainty indices (EPU),

along with their logarithmic transformations used in the HAR-type estimations.

Table 1: Summary Statistics for All Variables

Market	Variable	Mean	Std	Min	Max	Skewness	Kurtosis	JB <i>p</i> -val
USA	<i>GK_RV</i>	0.000076	0.000183	0.000000	0.005918	12.3851	241.3983	0.000
	<i>Ret_Sq</i>	0.000129	0.000463	0.000000	0.016295	15.2480	348.0835	0.000
	<i>VIX</i>	19.453991	7.764279	9.140000	82.690002	2.2045	8.6838	0.000
	<i>EPU</i>	115.385300	93.589371	3.320000	1026.380000	2.5388	9.5562	0.000
	$\ln(VIX)$	2.905020	0.341459	2.212660	4.415099	0.6681	0.5038	0.000
	$\ln(EPU)$	4.495732	0.710300	1.199965	6.933793	-0.0399	0.3931	0.000
India	<i>GK_RV</i>	0.000106	0.000394	0.000002	0.015028	23.0538	718.6663	0.000
	<i>Ret_Sq</i>	0.000157	0.000680	0.000000	0.026681	23.5584	761.6271	0.000
	<i>VIX</i>	19.766614	9.040230	9.150000	85.129997	2.3993	7.7127	0.000
	<i>EPU</i>	106.355767	51.636189	23.352756	323.807579	1.2229	1.9476	0.000
	$\ln(VIX)$	2.908564	0.364563	2.213754	4.444179	1.0256	1.0709	0.000
	$\ln(EPU)$	4.555710	0.475466	3.150715	5.780149	-0.0851	-0.2033	0.002
Brazil	<i>GK_RV</i>	0.000065	0.000073	0.000006	0.000780	4.5298	30.1343	0.000
	<i>Ret_Sq</i>	0.000093	0.000169	0.000000	0.001940	4.5159	30.4531	0.000
	<i>VIX</i>	28.872721	3.959900	21.000000	46.970001	1.4883	3.0398	0.000
	<i>EPU</i>	281.594633	166.438794	103.415149	891.557516	1.6693	3.3272	0.000
	$\ln(VIX)$	3.354379	0.127816	3.044522	3.849509	1.0015	1.4097	0.000
	$\ln(EPU)$	5.495705	0.524828	4.638751	6.792970	0.3881	-0.5475	0.000

Note: *GK_RV* and *Ret_Sq* represent the Garman-Klass and Simple Squared Return volatility measures, respectively. JB *p*-val refers to the *p*-value of the Jarque-Bera test for normality.

Based on the summary statistics reported in Table 1, several empirical regularities regarding the distributional characteristics of volatility and uncertainty measures can be observed. The mean realized volatility for India is notably higher than that of the U.S. and Brazil, suggesting that the Indian equity market experienced a more turbulent pricing environment during the sample period compared to its counterparts. Consistent with established stylized facts in financial econometrics, all volatility proxies exhibit severe leptokurtosis. Most notably, India displays an extreme kurtosis of 718.67, while the U.S. reaches 241.40. These values indicate a high frequency of extreme events and significant volatility clustering, which violates the assumptions of a standard normal distribution.

The Jarque-Bera test null hypothesis of normality is rejected for all series at the 1% significance level. This result justifies the application of logarithmic transformations to the *VIX* and *EPU* indices. As shown in the table, the logarithmic versions of these variables exhibit substantially lower skewness and kurtosis, effectively stabilizing the variance and mitigating the impact of outliers for the subsequent regression estimations. Across all three markets, both *EPU* and *VIX* exhibit positive skewness. This indicates that upward spikes in volatility and uncertainty are more frequent than large downward movements, aligning with the asymmetric nature of financial risk, according to Bekaert and Wu (2000). These descriptive findings reinforce the necessity of utilizing the HAR framework, as it is robust to the persistent and

non-normal characteristics of the underlying volatility data.

Table 2: Summary Statistics for Developed Markets (Supplementary)

Market	Variable	Mean	Std	Min	Max	Skewness	Kurtosis	JB p -val
Canada	GK_RV	0.000050	0.000211	0.000000	0.012492	28.2960	1330.3106	0.000
	EPU	185.1726	191.3740	28.5369	1635.4027	3.7935	19.0777	0.000
	$\ln(EPU)$	4.9230	0.7186	3.3512	7.3996	0.6121	0.3183	0.000
Japan	GK_RV	0.000089	0.000170	0.000000	0.006147	11.1989	245.5298	0.000
	EPU	105.2164	34.0144	45.6965	242.2823	1.3132	2.2277	0.000
	$\ln(EPU)$	4.6095	0.3001	3.8220	5.4901	0.3300	0.2252	0.000

Note: GK_RV denotes the Garman-Klass realized volatility. EPU represents the local Economic Policy Uncertainty index. JB p -val is the p -value of the Jarque-Bera test.

The descriptive statistics for another two markets, Canada and Japan (see Table 2), provide a crucial benchmark for evaluating the unique risk profiles of emerging economies. A striking observation is the distributional property of Canadian realized volatility (GK_RV), which exhibits an extreme kurtosis of 1330.31. While Canada maintains the lowest mean volatility (0.000050) across the five-country sample, this massive kurtosis, significantly higher than that of India (718.67) or the U.S. (241.40), suggests that the Canadian market is prone to rare high-magnitude volatility shocks despite its overall stability.

In contrast, Japan represents the most stable policy environment in the study. The Japanese EPU index displays the lowest standard deviation (34.01) and log-skewness (0.33), reflecting a highly predictable policy landscape. Canada's EPU, however, shows a higher mean (185.17) and notable right-skewness (3.79), capturing periods of heightened domestic policy debate.

Consistent with the findings in the primary markets, the Jarque-Bera test strongly rejects the null hypothesis of normality for all series in Canada and Japan ($p < 0.01$). Notably, the logarithmic transformation successfully recalibrates the EPU indices for both nations. The kurtosis for $\ln(EPU)$ drops precipitously to 0.318 for Canada and 0.225 for Japan. This normalization ensures the econometric robustness of the OLS-based HAR-X framework and validates the use of log-uncertainty measures in capturing the non-linear transmission of policy shocks.

4 Empirical Results and Analysis

This section presents a multi-layered empirical analysis of the relationship between EPU and stock market volatility across the U.S., India, and Brazil. We begin in Section 4.1 by establishing the baseline regression results, evaluating the efficiency of various volatility estimators and the incremental predictive power gained by incorporating the VIX and EPU indices. Section 4.2 extends this analysis to the international arena, specifically isolating the volatility spillover effects originating from U.S. policy uncertainty and its transmission to emerging markets. As market reactions are rarely linear, Section 4.3 employs a regime-dependent analysis to examine how sensitivity to EPU shifts during periods of high versus low market stress. To capture the temporal evolution of these relationships, Section 4.4 utilizes rolling window coefficient analysis, providing a granular view of how structural maturation and historical crises have reshaped domestic and cross-border uncertainty dynamics over time. Section 4.5 assesses the out-of-sample (OOS) predictive performance, validating whether the inclusion of exogenous spillover variables yields superior forecasting accuracy compared to standard benchmarks. Finally, Section 4.6 provides a supplementary comparative analysis of developed markets, specifically Canada and Japan, to serve as a benchmark for evaluating the unique vulnerability of emerging economies to global policy shocks.

4.1 Main Regression Results

The regression results for the five model specifications are summarized in Table 3. We examine the predictive role of external uncertainty factors across different market structures.

4.1.1 Comparative Efficiency of Volatility Estimators

The transition from Model 1 (Standard HAR with Simple Squared Returns) to Model 2 (GK-HAR with Garman-Klass RV) reveals a substantial increase in explanatory power across all markets. In the U.S., the R^2 improves from 0.239 to 0.365, while in India, it rises from 0.111 to 0.152. This validates the theoretical superiority of the Garman-Klass estimator, which utilizes intraday price ranges (OHLC data) to provide a more efficient measure of realized volatility compared to close-to-close squared returns. Consistent with the HAR framework, the weekly (RV_w) and daily (RV_d) components remain highly significant in most specifications, confirming the presence of volatility persistence and the heterogeneous nature of market participants.

4.1.2 The Incremental Role of VIX and EPU

Models 3 and 4 augment the GK-HAR framework with VIX and EPU , respectively. In Model 3, the coefficient for $\ln(VIX)$ is positive and statistically significant at the 1% level for all countries, indicating that forward-looking implied volatility captures distinct information regarding

future realized volatility. Model 4 investigates the impact of EPU , which shows a significant positive impact across all markets ($p < 0.05$), reflecting the sensitivity of financial markets to policy-related risks.

However, the full specification in Model 5 reveals a geographical divergence in how these risks are priced. In the USA, when VIX is controlled for, the coefficient of $\ln(EPU)$ becomes statistically insignificant ($p = 0.795$), suggesting that in mature markets, VIX effectively absorbs the risk premiums associated with policy uncertainty. In contrast, for Brazil, $\ln(EPU)$ remains statistically significant at the 5% level ($t = 2.079$) even in the presence of VIX . This indicates that in the Brazilian market, policy-driven uncertainty provides unique incremental information that is not fully reflected in market-based volatility indices. This shows the idiosyncratic nature of emerging market risks, where policy shocks have a direct influence on realized volatility independent of global market sentiment.

Table 3: HAR-type Regression Results across USA, India, and Brazil

Variables	Model 1 (SRV-HAR)	Model 2 (GK-HAR)	Model 3 (HAR-VIX)	Model 4 (HAR-EPU)	Model 5 (Full HAR-X)
<i>Panel A: USA</i>					
Daily (d)	0.1853***	0.1519***	0.1337***	0.1507***	0.1338***
Weekly (w)	0.3441***	0.4819***	0.4542***	0.4809***	0.4542***
Monthly (m)	0.2451***	0.1789***	0.0379*	0.1721***	0.0381*
$\ln(VIX)$	—	—	9.887e-5***	—	9.919e-5***
$\ln(EPU)$	—	—	—	6.740e-6***	-5.761e-7
R^2	0.239	0.365	0.384	0.365	0.384
<i>Panel B: India</i>					
Daily (d)	0.0587***	-0.0347**	-0.0383**	-0.0353**	-0.0385**
Weekly (w)	0.2870***	0.4117***	0.3915***	0.4102***	0.3915***
Monthly (m)	0.3394***	0.3482***	0.1834***	0.3306***	0.1800***
$\ln(VIX)$	—	—	0.0002***	—	0.0001***
$\ln(EPU)$	—	—	—	3.336e-5***	1.720e-5
R^2	0.111	0.152	0.163	0.153	0.164
<i>Panel C: Brazil</i>					
Daily (d)	-0.0393	0.2293***	0.1857***	0.2267***	0.1830***
Weekly (w)	0.0762	0.0598	-0.0623	0.0531	-0.0692
Monthly (m)	0.4224**	0.3329***	0.0223	0.2992***	-0.0122
$\ln(VIX)$	—	—	0.0002***	—	0.0002***
$\ln(EPU)$	—	—	—	1.036e-5**	1.049e-5**
R^2	0.020	0.121	0.173	0.127	0.179

Note: d, w , and m denote daily, weekly, and monthly lags of the respective volatility proxy (SRV for Model 1; GK_RV for Models 2–5). Statistical significance is indicated by *** ($p < 0.01$), ** ($p < 0.05$), and * ($p < 0.1$).

4.1.3 Multicollinearity Analysis

To ensure the reliability of the estimated coefficients in our full model (Model 5), we perform a multicollinearity analysis using the Variance Inflation Factor (VIF). While the HAR framework

inherently involves lagged variables that may exhibit high persistence, it is essential to verify that the inclusion of both market-implied volatility ($\ln VIX$) and economic policy uncertainty ($\ln EPU$) does not introduce excessive collinearity that could bias the results.

Table 4 presents the VIF values for all exogenous variables across the three markets. In econometric practice, while a VIF exceeding 10 is a traditional signal of structural multicollinearity (Kutner *et al.*, 2004), a more conservative threshold of 5 is often recommended to ensure the stability of coefficient estimates in high-frequency financial data (Hair *et al.*, 2010). Our empirical results show that all predictive variables, including the daily, weekly, and monthly realized volatility components, as well as the uncertainty indices, yield VIF values significantly below the conservative threshold of 5.

Specifically, in all three markets, $\ln EPU$ exhibits the lowest VIF (ranging from 1.07 to 1.10), suggesting that policy uncertainty provides a largely independent source of information. The highest VIF among predictors is observed for the weekly volatility component (RV_w) in the USA at 4.54, which is expected given the autoregressive nature of the HAR model but remains within the acceptable range for robust estimation.

Table 4: Variance Inflation Factor (VIF) Results for Model 5

Market	RV_d	RV_w	RV_m	$\ln(VIX)$	$\ln(EPU)$
USA	2.543	4.540	3.229	1.901	1.101
India	1.625	3.069	2.985	1.844	1.101
Brazil	1.651	2.443	2.095	1.988	1.074

Note: The table reports the VIF for each independent variable in the full HAR-X specification. An Intercept was included in the calculation but is not reported. All values are well below the threshold of 5, indicating no significant multicollinearity.

The robustness of our findings is further supported by comparing the coefficient of $\ln EPU$ between Model 4 (EPU only) and Model 5 (Full Model).

As shown in the analysis, while the inclusion of $\ln VIX$ in the U.S. and India leads to a reduction in the statistical significance of $\ln EPU$, the VIF remains low. This confirms that the observed crowding out effect in the U.S. (where $\ln EPU$ p -value shifts from 0.002 to 0.795) is a result of information overlap between the two uncertainty measures rather than a numerical artifact of multicollinearity.

In the case of Brazil, the coefficient for $\ln EPU$ remains stable (1.0×10^{-5}) and significant across both specifications, with a VIF of only 1.07. This further solidifies our conclusion that economic policy uncertainty provides an independent and unique predictive channel for market volatility in the Brazilian context, unaffected by the presence of other control variables.

4.2 Volatility Spillover Analysis: Impact of U.S. Economic Policy Uncertainty

In this section, we examine the international spillover effects of U.S. Economic Policy Uncertainty (US_EPU) on the realized volatility of Indian and Brazilian equity markets. Given the

status of the U.S. as a global economic anchor, shocks to its policy environment may affect emerging markets through trade, capital flow, and market sentiment channels. We extend the HAR-X framework by incorporating the U.S. daily EPU index alongside local control variables.

4.2.1 Spillover Regression Results

Table 5 reports the estimation results for the spillover models. To ensure robustness, we control for the local heterogeneous volatility components (RV_d, RV_w, RV_m) and the local forward-looking uncertainty index ($\ln Local_VIX$).

The empirical evidence reveals a significant geographical divergence in the susceptibility to U.S. policy shocks. For the Brazilian market, the coefficient of $\ln US_EPU$ is positive and statistically significant at the 1% level ($coef = 9.72 \times 10^{-6}, t = 2.732, p = 0.006$). This confirms a strong volatility spillover effect from the U.S. to Brazil, suggesting that investors in the Brazilian market price in U.S. policy risks as a significant factor in local market turbulence.

In contrast, the results for the Indian market indicate a lack of direct spillover from US policy uncertainty. While the local volatility components and local VIX remain highly significant, the coefficient for $\ln US_EPU$ is statistically insignificant ($p = 0.208$). This suggests that the Indian equity market may be more insulated from US-specific policy shocks, or that such risks are already subsumed by local market indicators and domestic policy factors.

Table 5: Spillover Effects of U.S. EPU on Emerging Market Volatility

Independent Variables	India (Nifty 50)	Brazil (Ibovespa)
Intercept	-0.0004*** (6.67e-05)	-0.0006*** (9.13e-05)
RV_d (Daily lag)	-0.0385** (0.018)	0.1796*** (0.045)
RV_w (Weekly lag)	0.3911*** (0.038)	-0.0661 (0.082)
RV_m (Monthly lag)	0.1787*** (0.048)	-0.0633 (0.116)
$\ln(Local_VIX)$	0.0002*** (1.99e-05)	0.0002*** (2.80e-05)
$\ln(US_EPU)$	1.061e-05 (8.43e-06)	9.724e-06*** (3.56e-06)
Observations	4,412	672
Adjusted R^2	0.163	0.175

Note: Standard errors are reported in parentheses. The dependent variable is the next-day realized volatility (RV_{t+1}). US_EPU represents the daily policy uncertainty index from the United States. Statistical significance: *** $p < 0.01$, ** $p < 0.05$.

The contrast between India and Brazil highlights the heterogeneous nature of financial integration among emerging economies. The significant spillover to Brazil can be attributed to

its high sensitivity to global commodity cycles and strong financial ties with U.S. capital markets. In this context, U.S. policy uncertainty acts as a proxy for global risk aversion, directly impacting Brazilian market stability. For India, the insignificant result reflects a market that is potentially more driven by internal structural dynamics and domestic policy uncertainty, as evidenced by our earlier findings where local EPU played a more prominent role.

4.2.2 Multicollinearity Analysis for Spillover Models

To validate the reliability of the observed spillover effects, we conduct a multicollinearity diagnosis on the joint set of predictors, which includes both local market indicators and the exogenous U.S. EPU index. This is particularly important for the spillover model, as global uncertainty often moves with local market fear gauges (VIX).

Table 6 reports the Variance Inflation Factors (VIF) for the spillover specifications. Consistent with our earlier local model diagnostics, all VIF values remain significantly below the threshold of 5. Notably, the VIF for $\ln(US_EPU)$ is exceptionally low in both markets (1.04 for India and 1.20 for Brazil), indicating that US policy uncertainty introduces a largely orthogonal (independent) source of information to the models.

Furthermore, we perform an auxiliary regression where the local $\ln(VIX)$ is regressed on $\ln(US_EPU)$. The resulting R^2 values are remarkably low: 0.0255 for India and 0.0677 for Brazil. This statistical evidence confirms that U.S. EPU and local implied volatility capture distinct facets of market risk, justifying their simultaneous inclusion in the HAR-X framework.

Table 6: VIF Results for Spillover Models (India and Brazil)

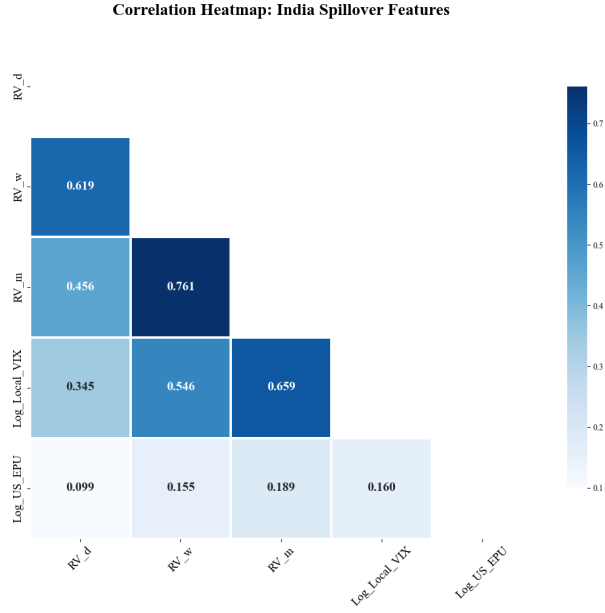
Market	RV_d	RV_w	RV_m	$\ln(Local_VIX)$	$\ln(US_EPU)$
India	1.625	3.070	2.996	1.786	1.040
Brazil	1.653	2.437	2.215	1.983	1.202

Note: The table reports centered VIF values. All values indicate the absence of problematic multicollinearity, ensuring the stability of the spillover coefficients.

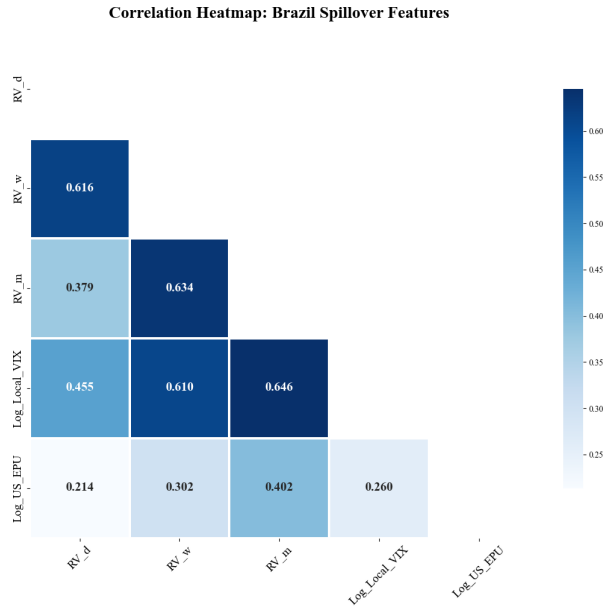
Figure 1 illustrates the correlation structure of the spillover features. The heatmaps confirm that while moderate correlations exist among the HAR components (RV_d, RV_w, RV_m), the correlation between U.S. policy uncertainty and local market variables is relatively weak, further supporting the robustness of our spillover analysis.

4.3 Regime-Dependent Analysis: Market Stress and EPU Sensitivity

To investigate whether the impact of economic policy uncertainty is contingent upon the overall market sentiment, we conduct a regime-dependent analysis. We partition the sample into two regimes based on the 75th percentile ($Q_{0.75}$) of the VIX index (or Local VIX for emerging markets) for each market: a *High Stress* regime ($VIX \geq Q_{0.75}$) and a *Normal Stress* regime



(a) India Spillover Features



(b) Brazil Spillover Features

Figure 1: Correlation Heatmaps for Spillover Model Features

($VIX < Q_{0.75}$). This allows us to test the hypothesis that EPU shocks are more potent during periods of heightened market vulnerability.

4.3.1 Sub-sample Evidence across U.S., India, and Brazil

The results of the sub-sample regressions for local policy uncertainty are summarized in Table 7.

The sub-sample analysis reveals a striking asymmetry in the US market. In the Normal

Table 7: Regime-Dependent Results for Local EPU (Threshold: 75th Percentile of VIX)

Market	Regime	Threshold (VIX)	Observations	EPU Coeff (P-val)	Adj.R ²
USA	High Stress	≥ 22.73	2,287	1.6e-05* (0.0575)	0.2883
	Normal	< 22.73	6,844	2.0e-08 (0.9238)	0.1257
India	High Stress	≥ 22.03	1,103	5.8e-05 (0.1521)	0.2017
	Normal	< 22.03	3,306	1.8e-05* (0.0747)	-0.0001
Brazil	High Stress	≥ 30.86	168	2.1e-05 (0.2314)	0.0887
	Normal	< 30.86	501	1.2e-05*** (0.0037)	0.0124

Note: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. The model includes $RV_{d,w,m}$ components.

regime, the EPU coefficient is effectively zero and statistically insignificant. However, in the High Stress regime, the EPU coefficient becomes positive and significant at the 10% level. This suggests that in the United States, policy uncertainty acts as a “tail risk” factor: it remains dormant during periods of market tranquility but begins to amplify realized volatility when investor fear (VIX) crosses a critical threshold.

4.3.2 Distinct Dynamics in Emerging Markets

The findings for India and Brazil contrast with the US experience. In India, the R^2 in the high-stress regime (0.2017) is substantially higher than in the normal regime, but the EPU itself does not reach significance in the stress state ($p = 0.1521$). This implies that during Indian market crises, volatility is driven more by the endogenous persistence of the market (the RV components). For Brazil, local EPU shows robust predictive power during calm periods ($p = 0.0037$), whereas in high-stress states, the signal is overshadowed by extreme volatility shocks.

4.3.3 State-Dependent Sensitivity and Interaction Effects

To test whether the impact of EPU significantly intensifies during periods of financial turbulence, we employ an interaction model. The model is specified as follows:

$$RV_{t+1} = \beta_0 + \beta_d RV_t + \beta_w RV_{t,w} + \beta_m RV_{t,m} + \delta_1 \ln(EPU_t) + \delta_2 High_VIX_t + \delta_3 (\ln(EPU_t) \times High_VIX_t) + \varepsilon_{t+1} \quad (4)$$

In this specification, δ_1 captures the impact of EPU during normal conditions, while δ_3 measures the incremental impact when the market is in a high-stress state ($VIX \geq Q_{0.75}$).

The results in Table 8 provide compelling evidence of nonlinear transmission. In the U.S., while the standalone EPU is negligible, the interaction term is highly significant at the 1% level. A similar effect is observed in India ($p = 0.034$). This establishes that policy-related news contributes to a vicious cycle of volatility only when investor sentiment is already fragile.

Table 8: Interaction Model Results: Local EPU and Market Stress

Variable	USA	India	Brazil
RV_d (Daily lag)	0.1431*** (0.013)	-0.0370** (0.018)	0.2004*** (0.046)
RV_w (Weekly lag)	0.4676*** (0.022)	0.4053*** (0.038)	-0.0237 (0.085)
RV_m (Monthly lag)	0.1113*** (0.022)	0.2633*** (0.045)	0.1880* (0.110)
$\ln(EPU)$	2.07e-08 (2.56e-06)	5.91e-06 (1.36e-05)	9.03e-06 (5.82e-06)
$High_VIX_Dummy$	-3.36e-05 (2.33e-05)	-0.0002 (1.27e-04)	-4.54e-05 (6.82e-05)
$\ln(EPU) \times High_VIX$	1.638e-05*** (5.01e-06)	6.39e-05** (3.01e-05)	1.37e-05 (1.23e-05)
R^2	0.3733	0.1591	0.1506
Adjusted R^2	0.3729	0.1579	0.1429

Note: Standard errors are reported in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. The dependent variable is RV_{t+1} . $High_VIX_Dummy$ is a binary variable based on the Q3 (75th percentile) of the local VIX index.

In contrast, for Brazil, both the standalone EPU (δ_1) and the interaction term (δ_3) fail to reach conventional levels of significance ($p = 0.122$ and $p = 0.267$, respectively). This suggests that domestic market volatility in Brazil is predominantly driven by its own historical persistence, particularly the daily lag (RV_d), rather than the state-dependent amplification of local policy uncertainty.

4.3.4 State-Dependency in U.S.-led Uncertainty Spillovers

Finally, we examine whether the spillover of U.S. policy uncertainty is also regime-dependent. This tests whether emerging markets are more sensitive to global policy shocks during periods of local turbulence.

The spillover results indicate that both India ($p = 0.036$) and Brazil ($p = 0.044$) exhibit significant state-dependency. For India, the U.S. EPU only has a significant impact when the domestic market is in a high-stress state. In Brazil, the already significant spillover effect is further amplified during periods of local fear. This shows the dual vulnerability of emerging markets: they are not only sensitive to domestic policy shocks but also become significantly more exposed to global (U.S.) policy uncertainty when their internal sentiment is fragile.

4.4 Rolling Window Coefficient Analysis: Time-Varying Dynamics

To capture the evolution of the impact of EPU over time, we employ a Rolling Ordinary Least Squares (Rolling OLS) approach. We utilize a fixed window of 252 trading days (approx-

Table 9: Interaction Model Results: U.S. EPU Spillovers and Local Market Stress

Independent Variables	India (Spillover)	Brazil (Spillover)
Intercept	1.665e-05 (4.47e-05)	4.261e-06 (1.97e-05)
RV_d (Daily lag)	-0.0366** (0.018)	0.1941*** (0.046)
RV_w (Weekly lag)	0.4034*** (0.038)	-0.0201 (0.083)
RV_m (Monthly lag)	0.2588*** (0.045)	0.0824 (0.114)
$\ln(US_EPU)$	3.765e-07 (9.48e-06)	6.928e-06* (3.87e-06)
$High_VIX_Dummy$	-0.0001 (0.0001)	-6.419e-05 (4.65e-05)
$\ln(US_EPU) \times High_VIX$	4.459e-05** (2.12e-05)	1.783e-05** (8.85e-06)
Observations	4,412	672
R^2	0.1588	0.1544
Adjusted R^2	0.1577	0.1468

Note: Standard errors are reported in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. The dependent variable is RV_{t+1} . $High_VIX_Dummy$ is an indicator variable based on the 75th percentile of the local VIX.

mately one business year) to estimate the time-varying coefficients for both domestic EPU impacts and international U.S.-led spillovers. This dynamic analysis allows us to identify specific historical periods where policy shocks became the dominant driver of market volatility.

The results of the 252-day rolling window regressions for domestic EPU across the U.S., India, and Brazil are visualized in Figure 2. This longitudinal perspective reveals significant structural shifts in how different equity markets price domestic policy risk.

4.4.1 Analysis of Local EPU Impact Dynamics

In the US market, the rolling coefficient for domestic EPU fluctuates near zero during stable periods but exhibits sharp and significant spikes during major systemic events. Notably, during the Global Financial Crisis (2008–2009) and the COVID-19 pandemic (2020), the coefficient surged, indicating that policy clarity becomes critical to market stability only during crises. Interestingly, the coefficient briefly turned negative in late 2021, suggesting a period where market participants may have become desensitized to policy news amidst broader inflationary concerns.

For the Indian market, significant policy impact was observed around 2010 and 2014, corresponding to major domestic legislative shifts and general elections. However, in recent years (2020–2026), the coefficient has stabilized near zero, reflecting an increasing maturation of the market where domestic policy shocks are more efficiently absorbed. In contrast, Brazil

Dynamic Impact of Domestic Policy Uncertainty

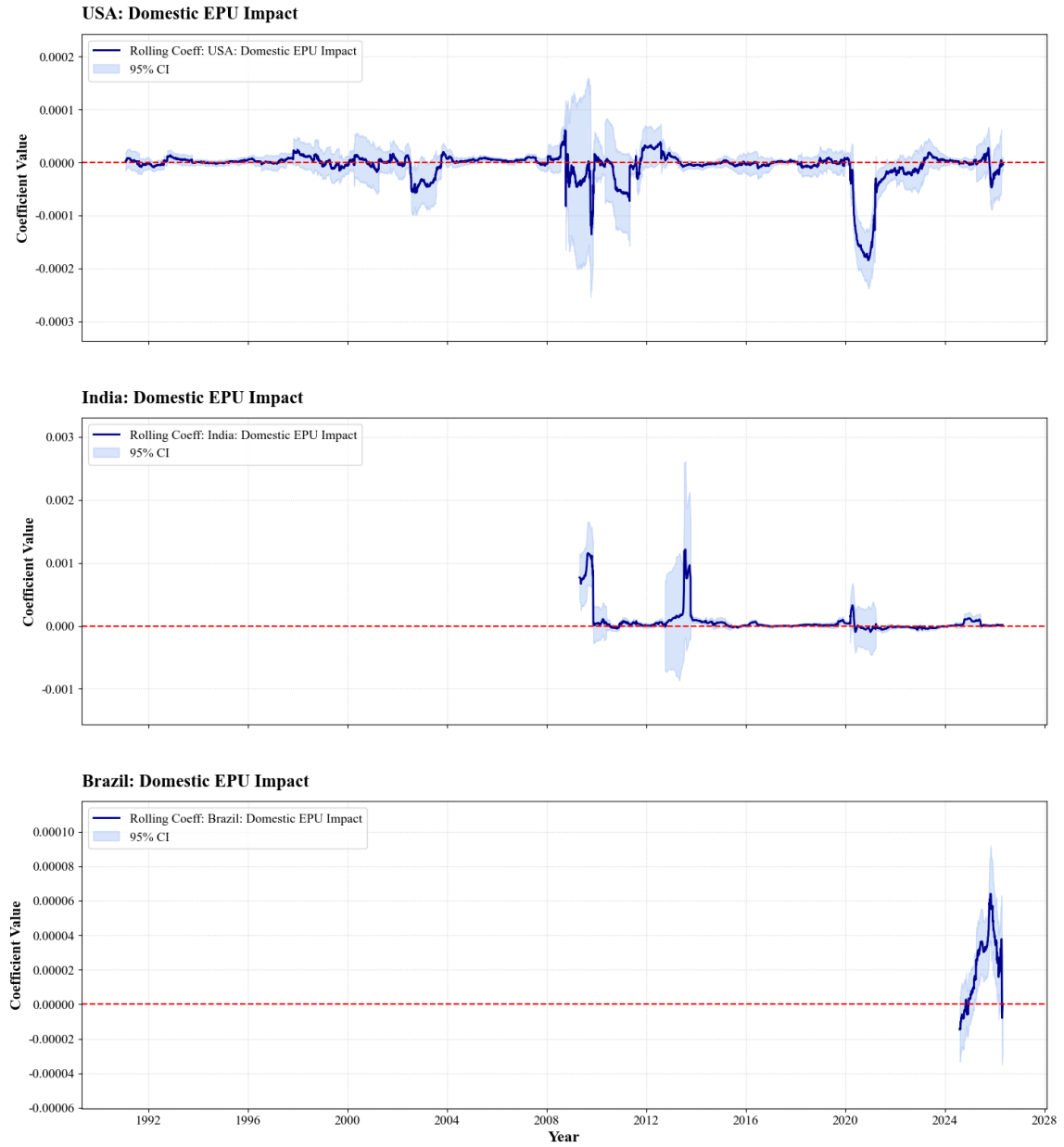


Figure 2: Dynamic Impact of Domestic Policy Uncertainty (252-day Rolling Window)

shows a dramatic rise in EPU sensitivity starting from 2024. This trend shows Brazil’s current vulnerability to domestic fiscal policy uncertainty.

4.4.2 Dynamic Spillovers from U.S. Policy Uncertainty

The international impacts of U.S. policy shocks is visualized in Figure 3. By benchmarking against the US domestic impact, we can evaluate the degree of “uncertainty contagion” across borders over a multi-decade horizon.

The spillover analysis confirms that U.S. policy uncertainty is a global risk factor, but its transmission is highly heterogeneous.

For India, the U.S. EPU spillover was most potent during the 2008 crisis and the 2020 pandemic. However, the coefficient exhibits significant “mean-reversion,” often returning to insignificance during non-crisis periods. This suggests that India primarily experiences “crisis-contingent” spillovers.

For Brazil, the spillover coefficient shows a remarkable upward trajectory in the most recent period (2024–2026). The high degree of alignment between Brazil’s domestic EPU sensitivity and its sensitivity to US spillovers indicates a “dual-shock” environment. For Brazilian investors, U.S. policy uncertainty (e.g., Fed rate path, trade policies) now serves as a primary driver of local equity volatility.

4.4.3 Summary of Dynamic Findings

The rolling window analysis reconciles the findings from our previous state-dependency models. The frequent crossing of the zero-line and the periodic spikes in 95% confidence intervals validate that EPU is not a constant regressor. Instead, its impact is episodic, intensifying during periods of global or domestic rebalancing. The recent divergence where the U.S. and India show stabilized low sensitivity while Brazil exhibits record-high sensitivity highlights the idiosyncratic risk profiles of emerging markets in the post-pandemic era. It should be noted, however, that because the Brazilian dataset only covers the period since 2023, these observations represent a relatively short-term trend that requires further long-term validation as more data becomes available.

4.5 Out-of-Sample Predictive Performance

To evaluate the economic significance and practical utility of incorporating economic policy uncertainty into volatility forecasting, we conduct an out-of-sample (OOS) evaluation. We utilize a static split where the first 80% of the observations serve as the estimation window, and the remaining 20% are used to assess predictive accuracy. We evaluate the models using two primary metrics: the Mean Squared Error (MSE) and the Quasi-Likelihood (QLIKE) loss function, the latter of which is particularly robust to the non-symmetric nature of volatility innovations.

Dynamic Spillovers from US Policy Uncertainty



Figure 3: Dynamic Spillovers from US Policy Uncertainty (252-day Rolling Window)

Table 10 summarizes the OOS performance for both local EPU models and US-led spillover models. The predictive gain is quantified by the R_{OOS}^2 , representing the percentage reduction in MSE relative to the base HAR-VIX model.

Table 10: Out-of-Sample Performance: Local vs. Spillover EPU Models

Market / Model	Base MSE	EPU-enhanced MSE	QLIKE (EPU)	R_{OOS}^2 (%)
<i>Panel A: Local EPU</i>				
USA	1.905e-08	1.904e-08	6060.35	0.05%
India	8.511e-09	8.367e-09	54930.81	1.68%
Brazil	1.005e-08	1.019e-08	-8.298	-1.40%
<i>Panel B: US Spillover</i>				
India	8.501e-09	8.355e-09	59641.23	1.72%
Brazil	1.000e-08	9.861e-09	-8.332	1.43%

Note: $R_{OOS}^2 = (MSE_{base} - MSE_{epu}) / MSE_{base}$. A positive value indicates that the inclusion of EPU improves predictive accuracy. The evaluation period covers the final 20% of the sample for each market.

4.5.1 Local Predictive Power

The results for the local models show a significant improvement in the Indian market, where the inclusion of domestic EPU reduces the forecast error by 1.68%. This suggests that Indian market participants react meaningfully to domestic policy signals in their trading behavior. For the U.S., the improvement is marginal (0.05%), consistent with our previous findings that VIX already encapsulates the majority of policy-related information in mature markets. Interestingly, the Brazilian local model shows a negative R_{OOS}^2 , indicating that while EPU is significant in-sample, its high volatility during the recent test period may introduce noise that complicates point forecasts.

4.5.2 The Superiority of Spillover Spillovers

The most compelling evidence for the importance of EPU emerges from the spillover analysis. For both India and Brazil, the inclusion of U.S. EPU as an exogenous predictor yields consistent predictive gains.

For India, the spillover model achieves an R_{OOS}^2 of 1.72%, the highest improvement across all specifications. This confirms that U.S. policy shocks are more informative for future Indian volatility than domestic Indian policy shocks.

For Brazil, in contrast to the local model, the US-led spillover model provides a positive R_{OOS}^2 of 1.43%. This suggests that global policy uncertainty (stemming from the U.S.) provides a more stable and reliable predictive signal for Brazilian equity volatility than idiosyncratic domestic factors during the forecast horizon.

4.5.3 Summary of OOS Findings

The out-of-sample results show that policy uncertainty is not only a descriptive variable but a predictive one. The robust performance of the spillover models in India and Brazil shows the high degree of financial integration and the central role of U.S. policy in the risk-pricing mechanisms of emerging markets.

While the marginal improvement in predictive power may appear modest in magnitude, these indices provide critical utility in anticipating macro-policy risks that are not fully captured by traditional market-based indicators. These findings suggest that risk managers and derivatives traders in these regions can achieve more accurate volatility forecasts and better risk-hedging strategies by incorporating U.S.-based uncertainty indices into their econometric frameworks. Furthermore, while daily EPU data is currently only available for the U.S., the potential predictive power of policy uncertainty is expected to grow as higher-frequency indices are developed for other markets. Improving the precision and reporting frequency of these metrics will likely allow for even more granular captures of policy-induced shocks in the future.

4.6 Supplementary Analysis: Developed Markets Comparison

To further validate the unique sensitivity of emerging markets to global policy shocks, we extend our analysis to two major developed economies: Canada and Japan. This supplementary comparison serves as a benchmark to assess whether the U.S.-led EPU spillover effect is a universal phenomenon or if its magnitude varies according to market maturity and institutional frameworks.

The results, presented in Table 11, reveal several critical insights. In the case of Canada, both domestic EPU and U.S. EPU spillovers have a significant positive impact on stock market volatility. Notably, the coefficient for U.S. EPU spillovers ($\delta = 6.645 \times 10^{-6}, p < 0.01$) is marginally larger than that of local EPU ($\delta = 5.245 \times 10^{-6}, p < 0.05$). This indicates a high degree of financial and economic integration, where U.S. policy uncertainty acts as a dominant risk factor, occasionally overshadowing domestic policy signals.

In contrast, the Japanese market exhibits a stronger sensitivity to domestic policy uncertainty. While the U.S. spillover effect is statistically significant ($\delta = 5.727 \times 10^{-6}, p < 0.01$), the coefficient for local EPU is substantially larger ($\delta = 3.398 \times 10^{-5}, p < 0.001$). This suggests that for a large and relatively autonomous economy like Japan, domestic structural policies and monetary shifts remain the primary drivers of equity risk, even though global uncertainty still plays a non-negligible role.

When compared to the findings for India and Brazil, the spillover coefficients for Canada and Japan are consistently lower in magnitude. This contrast supports our central hypothesis. While U.S. policy uncertainty is a global systematic risk factor, emerging markets exhibit a higher degree of vulnerability. The relatively lower coefficients in developed markets suggest

a more robust capacity to absorb external policy shocks, likely due to more mature hedging instruments and more stable institutional buffers.

Table 11: Supplementary Analysis: Local EPU vs. U.S. Spillover Effects (Developed Markets)

Market	Model Type	EPU Coef.	Std.Err	t-stat	p-value	Adj. R^2
Canada	Local EPU	5.245e-06**	(2.337e-06)	2.244	0.0249	0.3549
	Spillover EPU	6.645e-06***	(2.384e-06)	2.788	0.0053	0.3551
Japan	Local EPU	3.398e-05***	(5.387e-06)	6.306	0.0000	0.2171
	Spillover EPU	5.727e-06***	(2.182e-06)	2.625	0.0087	0.2144

Note: Significant levels: *** $p < 0.01$, ** $p < 0.05$. Standard errors are reported in parentheses. The dependent variable is the next-day realized volatility (RV_{t+1}). The total observations are 10,371 for Canada and 9,634 for Japan.

5 Discussion

The empirical evidence from this study provides a multi-dimensional mapping of how domestic and international EPU affects the volatility path of diverse equity markets. By reconciling static regressions, collinearity diagnostics, regime-dependency analysis, and dynamic rolling windows, this section explores the broader implications of uncertainty transmission and the structural vulnerabilities of emerging economies.

5.1 The “Uncertainty Multiplier”: Reconciling VIX and EPU

A central contribution of this study is the clarification of the relationship between market-implied fear (VIX) and policy uncertainty (EPU). While our VIF diagnostics (Table 4) confirmed that VIX and EPU are statistically distinct, the state-dependency analysis reveals a deep functional synergy.

In the U.S. market, the apparent insignificance of EPU in the full model was unmasked by the interaction analysis as a threshold effect. EPU operates as an “Uncertainty Multiplier” (Bloom, 2009): during periods of low market stress, institutional buffers absorb policy shocks; however, once the VIX breaches the 75th percentile (22.73), the predictive power of EPU surge ($p < 0.01$). This suggests that policy ambiguity does not only add to volatility, but compounds existing financial fragility, acting as a catalyst that transforms moderate market fluctuations into systemic tail-risk events.

5.2 The Dominance of U.S. Spillovers

The disparity between domestic EPU effects and U.S.-led spillover effects provides a critical lens for evaluating the “Global Financial Cycle” (Rey, 2013).

In terms of emerging market sensitivity, our spillover analysis (Table 5) demonstrates that U.S. policy uncertainty is a more potent and consistent driver for India and Brazil than their own domestic policy narratives. In Brazil, the U.S. EPU coefficient (9.724×10^{-6}) remains robustly significant even after controlling for local VIX, highlighting a direct transmission channel of global risk.

Also, the dynamic rolling regressions (Figure 3) provide visual evidence that during the 2008 GFC and the 2020 pandemic, the sensitivity of Indian volatility to U.S. EPU mirrored or even exceeded the sensitivity within the U.S. itself. This synchronized reaction suggests that emerging markets have failed to “decouple” from the US policy cycle. Instead, they remain deeply integrated into a U.S.-centric risk pricing framework.

Furthermore, the supplementary analysis of developed economies reveals that while U.S. EPU spillovers are globally pervasive, their impact is notably more restrained in Canada and Japan compared to the heightened sensitivities observed in India and Brazil, suggesting that market maturity and institutional stability act as critical buffers against external policy shocks.

5.3 Predictive Utility: Beyond Point Forecasts

The out-of-sample (OOS) evaluation (Table 10) provides a reality check for the economic application of our models. While the R_{OOS}^2 gains such as the 1.72% improvement in the India spillover model may appear modest, they carry substantial weight for risk management.

Standard volatility models (HAR-VIX) are inherently reactive, relying on past price clusters. Our results demonstrate that EPU serves as a proactive macro-filter. In India and Brazil, incorporating U.S. EPU consistently lowered the QLIKE loss, suggesting that EPU provides superior information regarding the “shape” of the volatility distribution, particularly in anticipating jumps. For institutional investors, EPU is not a tool for daily scalping but a strategic indicator for adjusting capital buffers before macro-regime shifts occur.

5.4 Policy Recommendations

For Regulatory Authorities, the finding that U.S. policy shocks dictate local volatility more than domestic factors suggests that emerging market central banks (RBI and BCB) should prioritize macro-prudential resilience to global shocks over the fine-tuning of domestic policy communications. Building “policy-resistant” financial systems involves strengthening FX reserves and liquidity backstops that can withstand the exogenous surges in U.S. EPU.

For Global Investors, our results indicate that diversification across emerging markets is an insufficient hedge against US policy risk. Since U.S. EPU acts as a systemic global factor affecting both India and Brazil in high-stress states, true diversification requires using U.S.-based volatility instruments (e.g., VIX futures) to hedge the tail-risks emanating from Washington, even when the underlying exposure is in the Global South.

6 Conclusion

This study conducted a cross-national empirical investigation to explore the complex relationship between EPU and financial market volatility. By shifting our analytical perspective from a purely domestic viewpoint to a cross-border spillover effect framework, we demonstrate that uncertainty is not only a localized phenomenon, but a systemic global risk factor. Our findings highlight the disproportionate impact of US policy shifts on emerging economies and show the conditional and nonlinear nature of risk transmission. The following sections summarize our key findings, discuss the contributions of this research, and outline future directions for academic research.

6.1 Summary of Findings

This study has provided an empirical examination of the impact of EPU on equity market volatility in the U.S., India, Brazil, Canada, and Japan. By integrating EPU indices into an augmented HAR-X framework and expanding the scope to transnational spillovers, our research yields conclusions below.

First, the U.S. functions as a global center for uncertainty. Our results demonstrate that U.S. EPU is a far more potent and consistent predictor of volatility in Brazil than its own domestic policy indicators. This confirms that emerging markets are deeply integrated into a U.S.-centric risk-pricing cycle.

Furthermore, we find that EPU is not a constant driver of market risk. In the U.S. and India, it operates as a threshold-activated variable, where its predictive power is dormant during tranquil periods but becomes statistically significant ($p < 0.05$) when market stress (VIX) exceeds the 75th percentile.

Additionally, the rolling window analysis reveals that the transmission of uncertainty is episodic, with peak sensitivity coinciding with global crises. Out-of-sample (OOS) tests further validate that incorporating U.S. EPU leads to tangible improvements in forecasting accuracy (up to 1.72% in R^2_{OOS} for India).

6.2 Contributions to Literature

We contribute to the existing financial literature by bridging the gap between volatility persistence models (HAR) and news-based uncertainty indices in a cross-country context. By utilizing the Garman-Klass (GK-RV) estimator, we provide a more robust measure of realized volatility than studies relying on simple squared returns. Furthermore, our multi-methodological approach combining VIF diagnostics, interaction models, and rolling OLS offers a more granular understanding of the time-varying nature of policy-induced risk than static linear frameworks.

6.3 Limitations

Despite the robust findings, several limitations of this study suggest directions for future research.

First, a significant constraint lies in the asymmetry of EPU data frequency and precision. Currently, only the U.S. possesses a high-frequency daily EPU index dating back to 1985. For many other economies, including major emerging markets, daily indices are often constructed using monthly interpolations or are unavailable for longer horizons. This discrepancy may lead to an underestimation of the immediate impact of local policy shocks. Future research would benefit greatly from the development of more granular and real-time uncertainty metrics across a broader range of countries to better capture high-frequency market dynamics.

Second, the sample size for certain emerging markets remains a limitation. For instance, the Brazilian dataset used in this study covers only a few hundred observations due to the recent inception of its VIX reporting. While our results provide a preliminary glimpse into Brazil's fiscal vulnerability, the short-term nature of the data means that these findings require long-term validation. As the historical coverage for these newer indices expands, future studies will be able to perform more rigorous structural break tests and business-cycle analysis.

Finally, while this study focuses on key representative economies like India and Brazil, there is a clear need to expand the analysis to a wider array of developing nations. The degree of financial integration and EPU sensitivity likely varies significantly across different regions. Although data availability remains uneven across the Global South, future work should strive to incorporate more diverse emerging markets into a unified spillover framework to test the universality of the U.S.-led uncertainty hypothesis.

6.4 Directions for Future Research

Future studies could benefit from decomposing the EPU index into specific policy domains (e.g., Monetary, Fiscal, or Trade) to identify which component of U.S. policy is the primary driver of international spillovers. Additionally, the integration of high-frequency sentiment analysis or machine learning techniques could further refine the non-linear relationship between policy narratives and market reactions.

6.5 Final Remarks

In an era characterized by “Polycrisis,” economic policy uncertainty has emerged as a fundamental determinant of financial stability. This study shows that the shadow of U.S. policy uncertainty extends far beyond its domestic borders, acting as a critical regime-dependent driver of risk in emerging markets. For global investors and policymakers, understanding this U.S.-led uncertainty contagion is no longer optional. Instead, it is a prerequisite for navigating the complexities of the modern financial landscape.

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Appendix: Statement on the Use of Artificial Intelligence

In this study, the large language model Google Gemini was used to debug Python code, improve paragraph clarity and coherence, and format paper layout in LaTeX.