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Spillovers of the U.S. Monetary Policy Uncertainty to India's Real Economy: A Channel-Specific ARDL Analysis

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Abstract

The Study empirically examines how uncertainty in the United States (U.S.) monetary policy affects India's industrial output through the interest rate channel. The analysis uses monthly data from 1997 to 2020 and applies the Autoregressive Distributed Lag (ARDL) bounds-testing approach to examine both short-run and long-run effects. The Toda–Yamamoto method is also used to confirm the direction of causality. Monetary policy uncertainty is measured through the index developed by Husted, Rogers and Sun (2017), while the Leo Krippner Shadow Short Rate (LKSSR) is used as a measure of the actual U.S. policy stance. The model also accounts for major crisis periods such as the Asian financial crisis, the dot-com collapse, the global financial crisis and the European debt shock. The results show that higher uncertainty in the U.S. policy reduces India's industrial production in both the short and long term. Nearly half of the adjustment towards equilibrium takes place within a month. Crisis periods make the impact stronger, which suggests that uncertainty shocks are more damaging when global conditions are weak. The impulse response patterns show that the decline in industrial output is sharpest about six to eight months after the shock and then settles by the second year. The dynamic multipliers confirm that the adjustment is gradual and persistent. The main contribution of the study is the joint use of a forward-looking uncertainty index and the shadow rate within a single, channel-specific framework. India's one-year treasury yield, which is highly correlated with India's policy rate, viz, repo rate, is used to represent domestic financial conditions, as it remains consistent across changing policy regimes.

Keywords: ARDL, Emerging Markets, Error Correction Model, India, Interest Rate Channel, International Transmission, Toda–Yamamoto Causality, U.S. Monetary Policy Uncertainty

JEL Classification: E52, E44, C32, F42, O53

1. Introduction

In today's global economy, monetary decisions taken in the United States influence financial conditions far beyond its own borders. Because the U.S. issues the main reserve currency and remains the centre of international finance, its policy actions shape global liquidity and cross-border investment flows (Rey, 2016). Much of the early work focused on how actual changes in the policy rate affect other economies. However, recent research has begun to stress an equally important aspect- monetary policy uncertainty (MPU). This refers to the uncertainty surrounding the direction, timing, or magnitude of future policy actions. Studies such as Husted, Rogers, and Sun (2017) and Mumtaz and Surico (2017) show that uncertainty itself can create disruptions that are sometimes more destabilising than the policy moves that eventually follow.

In the last decade, U.S. financial markets have witnessed sharp swings in interest-rate expectations, occasionally moving within short periods from anticipated tightening to an expected easing cycle. These frequent shifts make it

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difficult for global investors to form a clear sense of where policy is headed. When uncertainty increases, investors tend to move funds into safer U.S. assets. This has direct consequences for emerging economies, where capital becomes costlier and financing conditions tighten. India feels these pressures quite quickly because its financial markets are increasingly integrated with global capital flows. Borrowing costs move up, credit conditions tighten, and business confidence weakens. This study focuses on these concerns by examining how U.S. MPU affects India's industrial production through the interest-rate transmission channel. The analysis distinguishes between the impact of uncertainty and the effect of the actual U.S. policy stance, following assessments by the International Monetary Fund (2023), the Bank for International Settlements (2024), and the Reserve Bank of India (2023). The sample ends in January 2020 to avoid the distortions brought about by the pandemic-related shocks, which created structural breaks in most macroeconomic time series (Lütkepohl, 2005).

MPU can arise from several sources such as conflicting macroeconomic data, unclear policy communication, or changes in global risk sentiment. When uncertainty rises, financial markets find it harder to form expectations about where the policy rate is heading, and this usually leads to more volatility in interest rates, exchange rates, and asset prices (Pastor & Veronesi, 2021). Central bank communication matters as well. Shrimali (2025) shows that when communication is inconsistent or unclear, uncertainty increases, and this tends to magnify the effect of external shocks on emerging economies. For countries like India, which are dependent on foreign capital and open to cross-border flows, these disturbances affect investment decisions and broader macroeconomic conditions (Lakdawala, Moreland, & Schaffer, 2020). As Gopinath (2025) notes, emerging economies often operate with limited buffers, which makes them more exposed to swings in global financial conditions.

Among the various international transmission channels, the interest-rate channel remains one of the most important. A rise in U.S. MPU tends to push up global risk premia, encouraging investors to move into U.S. assets and increasing borrowing costs in emerging markets (Bernanke & Blinder, 1992; Lastauskas & Nguyen, 2021). Higher financing costs can slow investment and reduce industrial activity. Since industrial production is a key driver of growth and employment in India, understanding this channel has clear policy value.

Although MPU spillovers have been widely studied, most work either focuses on advanced countries or groups emerging markets together. India specific work remains limited, and many studies rely only on observed changes in the U.S. policy rate, which does not capture the forward-looking nature of uncertainty shocks (Sengupta & Vardhan, 2017; Bhattarai, Chatterjee, & Park, 2020). Only a few papers use structured uncertainty measures, such as Husted et al. (2017) to examine channels separately.

This study contributes to the literature in three ways. First, it examines the influence of U.S. MPU on India's industrial production through the interest-rate channel, combining a forward-looking uncertainty index with a policy-stance indicator that works in both conventional and unconventional periods (LKSSR). Second, it controls for India's domestic short-term interest rate to isolate the interest-rate channel clearly, instead of letting multiple channels overlap. Third, by focusing on the pre-COVID period, the study avoids the unusual distortions of pandemic-era policy interventions while still covering several U.S. monetary policy cycles. Global controls (oil prices and global GDP) and major crisis dummies add further robustness to the design.

The findings indicate that U.S. MPU has a clear and measurable effect on India's industrial activity. In the long run, higher MPU lowers industrial production, mainly through tighter financial conditions and increased borrowing costs. Short-run effects appear within a few months and tend to ease gradually. The shadow short rate, which captures the actual policy stance, also shows a negative association with industrial output, while global GDP supports growth. Major global crises such as the Asian financial crisis and the global financial crisis tend to heighten these effects. Overall, the results point to the interest-rate channel as a key pathway through which global uncertainty reaches India's real economy (Mumtaz & Surico, 2017; Bhattarai, Chatterjee, & Park, 2020; Kohlscheen & Miyajima, 2022).

The remainder of the paper proceeds as follows: Section 2 presents a brief review of the literature, while Section 3 describes the methodology followed in the study and the database used for empirical estimation. Section 4 reports the descriptive statistics and undertakes a preliminary analysis of the data, while further details on empirical results are given in Section 5. Section 6 presents the summary and conclusions of the analysis.

2. Review of Literature

This section reviews both theoretical and empirical literature on MPU, beginning with international evidence and then turning to studies that focus on India. The discussion highlights how MPU shapes macroeconomic and financial outcomes in emerging markets and identifies the gaps that this study seeks to address.

2.1 Theoretical Foundations: The Interest Rate Channel of MPU

In an open economy, domestic financial conditions are shaped not only by local policy but also by global developments. The Mundell-Fleming framework illustrates how changes in foreign interest rates or even expectations about their future path are transmitted to domestic credit markets through capital flows and exchange rate adjustments (Mundell, 1963; Fleming, 1962). Policy uncertainty amplifies this mechanism. When the direction of U.S. monetary policy is unclear, markets demand higher risk premia, investors shift toward U.S. treasuries, and emerging economies experience tighter credit and higher borrowing costs (Husted, Rogers, & Sun, 2017; Pastor & Veronesi, 2021). For India, these dynamics often translate into weaker investment and industrial production, as firms delay commitments under heightened uncertainty (Bernanke, 1983; Woodford, 2003).

Global financial cycles further reinforce the interest rate channel. The stylised transmission mechanism of the US monetary policy uncertainty to the Indian economy is shown in Figure 1. The U.S. monetary conditions, especially during uncertain periods, strongly influence global capital flows and leverage (Rey, 2016). It is therefore essential to distinguish between the stance of U.S. monetary policy captured by the LKSSR (Krippner, 2015) and the uncertainty around it. Both the policy stance and the uncertainty associated with it can transmit contractionary effects to emerging markets, through different pathways. Further, these effects are not constant over time. Episodes such as the Asian financial crisis, the dot-com bubble, the global financial crisis and the European debt crisis intensified global risk aversion and liquidity pressures, amplifying the domestic impact of U.S. monetary shocks. Any empirical assessment of MPU must therefore account for structural breaks to avoid overstating or misattributing effects.

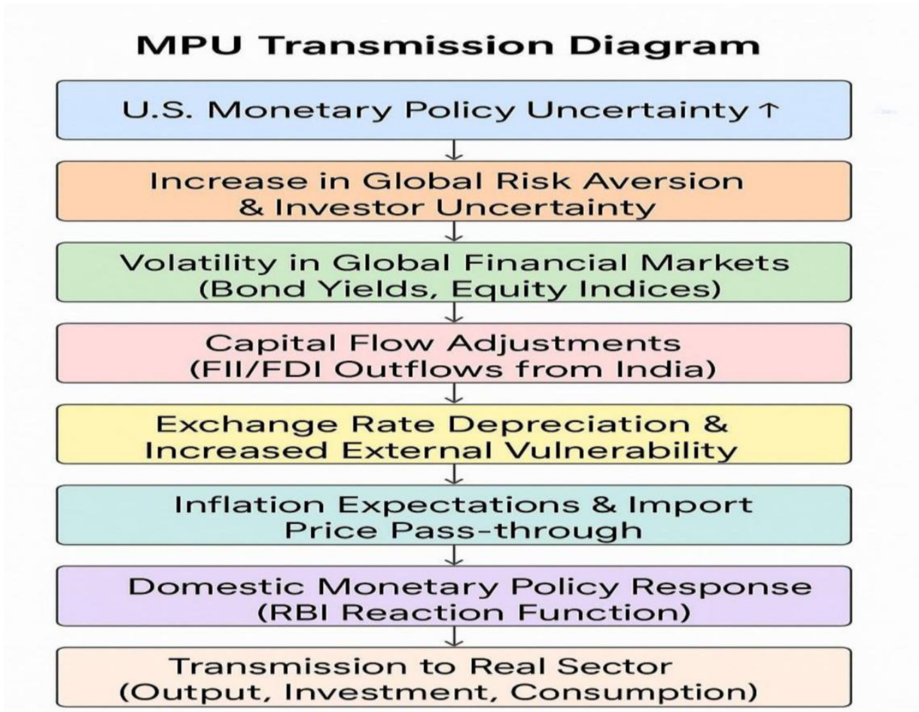
2.2 International Evidence on the Effects of Monetary Policy Uncertainty

International research on MPU has grown rapidly in the post-crisis period, as central banks increasingly relied on unconventional tools and forward guidance. Early contributions such as Greenspan (2004) noted that financial markets respond not only to policy actions but also to the ambiguity surrounding central bank intentions. Subsequent empirical work by Jurado, Ludvigson, and Ng (2015) formalised the measurement of macroeconomic and policy uncertainty, showing that heightened uncertainty depresses investment, output, and consumption. Building on this framework, Husted, Rogers, and Sun (2017) developed a U.S. specific MPU index and demonstrated that unexpected increases in uncertainty widen credit spreads, weaken industrial production, and reduce equity valuations.

More recent studies offer a broader view of the international spillovers of U.S. MPU. Engler, Piazza, and Sher (2023) found that U.S. monetary announcements and economic news exert powerful effects on emerging-market financial conditions, even in the absence of policy-rate adjustments. Their evidence suggests that uncertainty alone can tighten financial conditions in countries exposed to global capital flows. Lastauskas and Nguyen (2021) reached a similar conclusion, noting that emerging markets experience deeper and more persistent downturns when monetary tightening coincides with elevated uncertainty. Checo, Grigoli, and Sandri (2024) reinforced this pattern, showing that interest-rate and credit channels amplify external shocks in economies where financial systems are still evolving.

At the broader emerging-market level, Shrimali (2025) highlights the role of central bank communication in shaping uncertainty dynamics. Inconsistent or incomplete guidance from monetary authorities tends to heighten uncertainty, which in turn magnifies the impact of global shocks on domestic financial markets. Evidence from South Asia further illustrates these vulnerabilities. Singh and Mehta (2023) showed that unconventional monetary policies originating in advanced economies reverberate through interest-rate, exchange-rate, and asset-price channels across South Asian emerging markets, underscoring the structural susceptibility of the region to global policy cycles.

Additional literature also emphasises the asymmetric effects of uncertainty. Mumtaz and Surico (2017) report that uncertainty shocks lead to larger output losses during recessions than in expansions. Balcilar, Gupta, and Wohar (2021) note that U.S. policy uncertainty raises financial



Source: Authors' illustration based on theoretical insights from Bernanke *et al*. (1999), Husted, Rogers, and Sun (2020), and empirical frameworks used in emerging markets transmission studies (Aizenman *et al*., 2016; Ahmed & Zlate, 2014)

Figure 1. Stylised transmission mechanism of the U.S. monetary policy uncertainty to the Indian economy.

volatility across emerging markets. Pastor and Veronesi (2021) show that heightened uncertainty elevates risk premia, triggering portfolio reallocations toward safer assets. Caldara et al. (2022) document that global financial markets adjust rapidly to uncertainty shocks, with equity and bond markets showing pronounced volatility responses.

The global financial-cycle literature offers a broader interpretation of these findings. Rey (2016) argue that U.S. monetary conditions effectively anchor the global cost of capital, implying that uncertainty surrounding U.S. policy decisions influences risk-taking worldwide. Beckmann and Czudaj (2022) add that sentiment, often shaped by media narratives, amplifies the transmission of U.S. uncertainty to emerging-market assets. Reinforcing this view, recent analysis by Glebocki and Keefe (2024) shows that uncertainty shocks spread quickly across emerging markets through financial and trade linkages, demonstrating the international reach of U.S. monetary conditions.

2.3 Evidence from India and Emerging Markets

Compared with advanced economies, research on the effects of MPU in India remains relatively limited, although interest has increased significantly in recent years. Lakdawala, Moreland, and Schaffer (2020) showed that heightened U.S. uncertainty reduces portfolio inflows into India, with the effects intensifying during global stress episodes. Lastauskas and Nguyen (2021) reported that uncertainty-driven U.S. monetary shocks result in currency depreciation, increased inflationary pressures, and tighter domestic financial conditions across Asia, with India being one of the most affected economies. Bhattarai, Chatterjee, and Park (2020) also observed that uncertainty raises India's external financing costs, especially given the economy's dependence on foreign capital and imported energy.

Newer studies provide more granular evidence on India's financial markets. Patnaik, Felman, and Mishra (2023) found that U.S. uncertainty shocks lift India's sovereign bond yields and shorten the maturity structure of external borrowing. Chatterjee and Ray (2023) reported that India's industrial production responds more sharply to uncertainty during phases of elevated global risk aversion. Bhanumurthy and Seth (2023) confirm that uncertainty-induced monetary shocks in the United States affect the Indian yield curve even when the Reserve Bank of India (RBI) keeps its own policy rate unchanged.

Additional evidence suggests that global uncertainty directly influences Indian financial markets. Kundu and Sahu (2021) showed that episodes of heightened global uncertainty significantly increase India's market volatility through GARCH-based channels. On the macroeconomic side, international spillovers appear stronger during global crisis periods. Aizenman, Binici and Hutchison (2016) reported that uncertainty shocks deepen contractions in emerging markets when global risk aversion is high. Banerjee and Nag (2022) observed that the pass-through from U.S. uncertainty to India's inflation and exchange-rate pressures intensifies during domestic inflation surges, implying state-dependent transmission.

Official assessments mirror these academic findings. The RBI's Monetary Policy Report (2023) acknowledges that external uncertainty from advanced-economy monetary policy transmits to India's money-market rates, corporate yields, and credit conditions, often without changes in the domestic policy rate. This recognition aligns with the broader empirical conclusion that India's real economy is increasingly influenced by uncertainty shocks rather than simple policy-rate adjustments.

2.4 Identified Gaps

Although earlier studies recognise that U.S. MPU affects India, empirical work remains incomplete. Most Indian studies still use the federal funds rate or broad uncertainty indices, instead of structured and forward-looking measures like the Husted, Rogers and Sun (2017) MPU index. Only a few papers study the interest-rate channel directly, even though both theory and recent evidence show that this is the main route through which external uncertainty changes domestic borrowing costs.

Recent works on emerging markets also highlight financial-market spillovers, but they usually treat India as part of a larger regional sample rather than as a standalone case (e.g., Engler *et al*., 2023; Checo *et al*., 2024). Very few studies examine India using a model that separates policy stance from policy uncertainty. The LKSSR, which captures both conventional and unconventional U.S. monetary policy, has almost never been used in combination with MPU in the Indian context. As a result, past findings may be unable to show whether the shock comes from the level of U.S. policy or from uncertainty about future moves.

Another gap is the treatment of structural breaks. Many studies do not account for major crisis periods such as the Asian financial crisis, the dot-com correction, or the global financial crisis, even though these episodes can change the strength of transmission. Studies that ignore such shifts may give biased estimates.

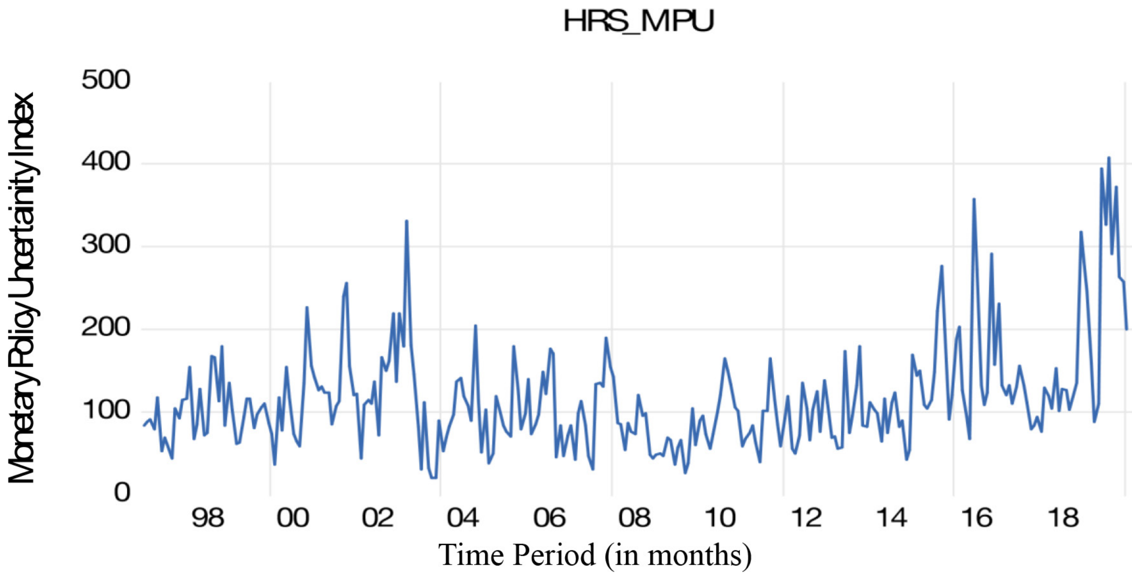
The present study fills these gaps by building a channel-specific ARDL model that jointly includes MPU and LKSSR, along with global controls and crisis-dummy variables. By isolating the interest-rate channel and focusing only on India, the study offers clearer evidence on how U.S. uncertainty shocks influence domestic industrial activity—an area that is still under-explored in Indian empirical research.

3. Methodology and Database

The study examines only the interest-rate channel because it is one of the main ways through which external monetary shocks affect borrowing costs, credit conditions, and real activity in India. The key explanatory variable is the MPU index developed by Husted, Rogers, and Sun (2017). This index measures uncertainty about the future path of U.S. monetary policy using the dispersion of interest-rate forecasts and therefore captures expectations rather than just announced policy moves. Previous studies on India have used the federal funds rate or other observable policy indicators, which do not reflect the forward-looking nature of uncertainty shocks (Bhattarai, Chatterjee & Park, 2020).

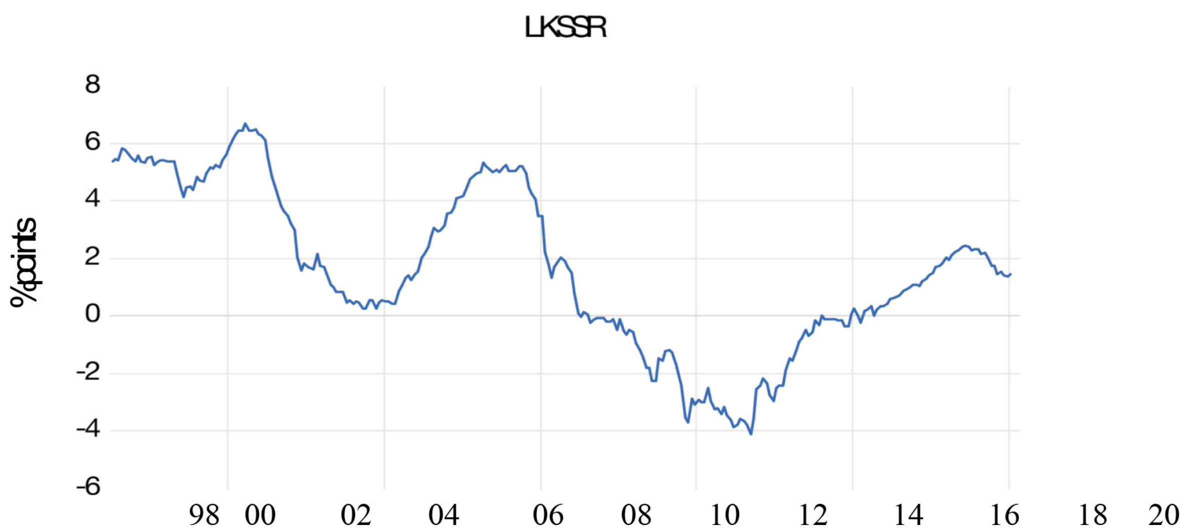
The MPU series is retained in its original level form in Figure 2, as the presence of negative values prevents log-transformation. Prior to estimation, its time-series characteristics were examined using standard unit-root diagnostics, including the Augmented Dickey–Fuller and Phillips–Perron tests (Dickey & Fuller, 1979; Phillips & Perron, 1988), to ensure suitability for the ARDL framework. The use of the ARDL bounds testing procedure is appropriate in this context, as it accommodates regressors with mixed integration orders and aligns with established time-series modelling guidelines outlined by Harris and Sollis (2003). The index in Figure 2 reflects forecast dispersion and spikes during episodes of global turbulence such as the Asian financial crisis, the global financial crisis, and the Taper Tantrum (Husted, Rogers & Sun, 2017).

To complement the MPU measure, the LKSSR series-presented in Figure 3 is incorporated as an indicator of the underlying stance of U.S. monetary policy, particularly during periods in which conventional



Source: Author's representation based on CEIC and FRED data

Figure 2. U.S. monetary policy uncertainty index, 1997–2020.

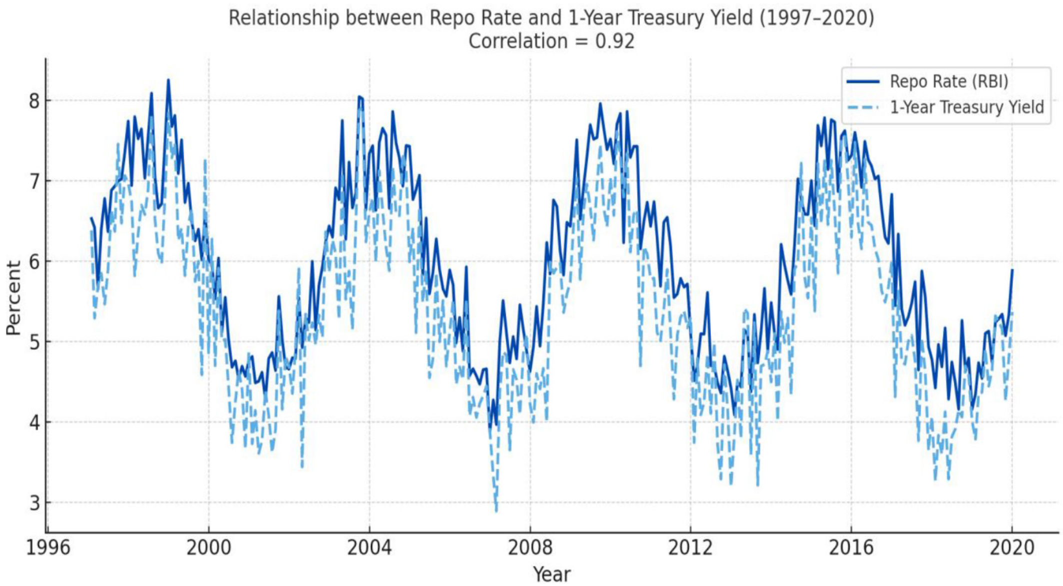


Source: Authors' representation based on data on LKSSR from Reserve Bank of New Zealand and Krippner dataset

Figure 3. Leo Krippner shadow short rate, 1997–2020.

short-term rates were constrained by the zero lower bound. By capturing the effects of unconventional policy tools, including large-scale asset purchases, the LKSSR provides a more comprehensive representation of policy accommodation than the federal funds rate over the sample period (Krippner, 2015). Its use is aligned with the established shadow-rate literature, which emphasises the importance of shadow policy indicators in assessing monetary conditions during non-standard policy regimes (Lombardi & Zhu, 2018). In Figure 3 the series declines sharply during the global financial crisis and remains below zero throughout much of the post-2008 period.

A critical part of the model is India's short-term domestic interest rate (lnINT), which is represented by the yield on government securities with a maturity of up to one year. This choice rests on two key reasons. First, the one-year yield moves very closely with the repo rate determined by RBI across different policy regimes, showing a strong correlation of about 0.92 over the sample period 1997–2020 as can be clearly seen in Figure 4. This relationship confirms that the one-year treasury



Source: Authors' representation based on RBI and CEIC data

Figure 4. Relationship between repo rate and 1-year treasury yield (1997–2020).

yield effectively captures the operative stance of monetary policy and serves as a reliable short-term rate proxy. Second, because the study period covers years when the repo rate was not always the main policy tool, depending only on it could give a misleading view of India's monetary position. In contrast, the one-year treasury yield reflects both policy signals and liquidity conditions in the market, providing a more comprehensive view of borrowing costs. Including this variable in the model helps ensure that the estimated impact of U.S. MPU reflects the external interest-rate channel and not shifts in India's own domestic stance (Mishkin, 1996; Rey, 2016).

The model further incorporates two global controls: (i) global-GDP (lnGGDP), which reflects world demand conditions and international business cycle fluctuations, and (ii) global oil prices (lnOIL), represented by Brent crude prices, given India's vulnerability as a large oil importer (Hamilton, 2003). Both variables are expressed in natural logarithms for elasticity interpretation and to improve statistical properties. Finally, the model explicitly conditions on India's short-term domestic interest rate (lnINT), which reflects internal monetary settings. This ensures that the estimated transmission of MPU is not confounded by India's own policy stance, thereby isolating the external channel (Mishkin, 1996; Rey, 2016).

The long-run ARDL model for the interest rate channel is specified as follows:

$$y_t = \alpha_0 + \alpha_1 MPU_t + \alpha_2 LKSSR_t + \alpha_3 InOIL_t + \alpha_4 InGGDP_t + \alpha_5 InINT_t + \sum \mu_j DUM_j + \varepsilon_t \quad \textbf{(1)}$$

The short-run ECM representation is:

$$\Delta y_t = \beta_0 + \sum_{i=1}^{\rho} \beta_i \Delta y_{t-i} + \sum_k \gamma_k \Delta x_{k,t-i} - \lambda EC_{t-1} + \sum \delta_j \Delta DUM_{j,t} + u_t \quad (2)$$

Here, y_t denotes the domestic macroeconomic indicator (industrial production), MPU_t is the uncertainty index, $LKSSR_t$ is the shadow short rate, DUM_j are binary variables for crises, and EC_{t-1} is the lagged error correction term. A statistically significant negative λ indicates convergence to the long-run equilibrium (Banerjee, Dolado, & Mestre, 1998).

The empirical procedures for unit root testing, lag selection, and diagnostic evaluation follow established econometric guidelines outlined by Gujarati and Porter (2009). Optimal lag-lengths are selected using the Akaike Information Criterion (AIC), which is particularly suitable for monthly datasets (Lütkepohl, 2005). Diagnostic checks and stability assessments via Cumulative Sum (CUSUM) and Cumulative Sum of Squares (CUSUMSQ) (Brown, Durbin, & Evans, 1975) are also undertaken. Dynamic multipliers and Impulse Response Functions (IRFs) are derived from the ARDL–ECM to assess the effect of a one standard deviation MPU shock on industrial production over 12–24 months, with bootstrapped confidence intervals (Jordà, 2005). It is expected that MPU shocks lead to tighter financial conditions and subdued investment, producing a contraction in real activity (Bloom, 2009).

For checking the robustness of the results, we apply the Toda and Yamamoto (1995) Granger-causality framework. This method estimates a VAR model in levels and then adds extra lags equal to the highest order of integration found among the variables. By doing so, we avoid the usual bias that appears when tests require pre-testing for cointegration. The approach gives valid causality results even when certain series are I(0) and the others are I(1) (Banerjee, Dolado, & Mestre, 1998).

The MPU variable is found to be stationary, while industrial production, the LKSSR, and global oil prices are integrated of order one. The Toda-Yamamoto method, therefore, fits the data structure well. It is more reliable than the traditional Granger test, which assumes full stationarity. Using this framework also helps separate the effects of MPU from those of policy stance (LKSSR). When combined with the ARDL bounds testing approach, the Toda-Yamamoto method offers a full picture of both the long-run equilibrium and the short-run causal link between U.S. monetary policy uncertainty and India's industrial output (Mavrotas & Kelly, 2001; Giles, 2011).

3.1 Database

For empirical estimation, we take monthly data spanning January 1997 to January 2020, deliberately excluding the COVID-19 period. The exclusion is methodologically motivated, as the pandemic introduced unprecedented structural breaks and extraordinary policy interventions that could distort established macroeconomic relationships (Lütkepohl, 2005). The chosen horizon captures both conventional and unconventional phases of U.S. monetary policy, including episodes of near-zero interest rates, quantitative easing, and major international crises. This provides a sufficiently rich sample to examine the impact of U.S. MPU on India's economy under diverse global monetary regimes (Krippner, 2015; Husted, Rogers, & Sun, 2017).

The study period is chosen to maintain consistency in the data and avoid distortions caused by the COVID-19 crisis and later geopolitical shocks. After 2020, fiscal and monetary actions across countries became highly unusual. Policies such as large liquidity injections and emergency lending blurred normal transmission patterns (IMF, 2023; BIS, 2024). Including those years could give biased results as the structure of both Indian and U.S. policy changed sharply. The selected period still captures many different policy regimes, from normal rate cycles to unconventional policy easing, without the extreme effects of the pandemic years. The data sources for all the variables are explicitly listed in Table A of the Appendix.

4. Preliminary Analysis

This section presents certain preliminary diagnostics of the dataset, such as descriptive statistics, stationarity tests, and lag-length selection. These steps are essential for validating the suitability of the ARDL framework and ensuring the robustness of subsequent empirical estimates.

4.1 Descriptive Statistics

Table 1 summarises the descriptive statistics for the variables used in the interest rate channel framework-industrial production (lnIIP), U.S. MPU, the LKSSR, global GDP (lnGGDP), Global Oil Prices (lnOIL), and India's short-term Interest Rate (lnINT).

The results indicate moderate variability in industrial production, oil prices, and interest rates, consistent with the combined influence of domestic cycles and external shocks

Table 1. Descriptive statistics (1997m01–2020m01).

Variable	Mean	Std. Dev.	Min	Max	Skewness	Kurtosis	JB Test (p-Value)
lnIIP	4.52	0.18	4.10	4.85	0.35	2.70	0.12
MPU	0.04	0.48	1.25	1.75	0.42	3.15	0.09
LKSSR	0.82	2.30	3.80	5.60	0.55	2.95	0.15
lnGGDP	4.95	0.07	4.80	5.10	0.10	2.55	0.20
lnOIL	4.05	0.45	3.20	4.95	0.25	2.90	0.18
lnINT	1.92	0.30	1.30	2.45	0.20	2.65	0.10

Note: JB = Jarque–Bera test for normality (see Table 1). MPU shows considerable fluctuations around zero, reflecting its design as a forward-looking measure of uncertainty (Husted, Rogers, & Sun, 2017). While some departures from normality are detected, this is common in macroeconomic time series (Nelson & Plosser, 1982) and does not affect the validity of ARDL estimation.

4.2 Unit Root Tests

To avoid spurious regressions, the stationarity of each variable was assessed using the Augmented Dickey-Fuller (ADF; Dickey & Fuller, 1979), Phillips-Perron (PP; Phillips & Perron, 1988), and KPSS tests (Kwiatkowski *et al.*, 1992). The results are reported in Table 2.

Table 2 shows a mix of integration orders: MPU is stationary at the level, while lnIIP, LKSSR, lnGGDP, lnOIL, and lnINT become stationary after first differencing. Importantly, no variable is I(2), justifying the use of the ARDL bounds testing framework (Pesaran, Shin, & Smith, 2001).

4.3 Lag-Length Selection

The optimal lag-structure was determined using the AIC, which is considered more suitable for high-frequency (monthly) data than the more conservative Schwarz criterion (Lütkepohl, 2005).

The selected ARDL(2,1,1,1,1) specification (given in Table 3) captures both immediate and lagged effects of shocks on industrial production while avoiding parameterisation. This choice reflects the persistence of India's industrial output and ensures that global and domestic dynamics are properly incorporated

5. Empirical Results

This section reports the results from the ARDL framework that links the U.S. MPU to India's industrial production through the interest rate channel. The study proceeds from the bounds test to long-run estimates, to short-run adjustment dynamics, and then to the role of crisis episodes. Inference uses robust standard errors and monthly data from 1997M01 to 2020M01.

5.1 Bounds Test for Cointegration

As the variables are a mix of I(0) and I(1) and none is I(2), the ARDL bounds approach of Pesaran, Shin, and Smith (2001) is appropriate. The F-statistic (see Table 4) exceeds

Table 2. Unit root test results (p-values).

Variable	ADF (Level)	ADF (1st Diff)	PP (Level)	PP (1st Diff)	KPSS (Level)	KPSS (1st Diff)	Integration Order
lnIIP	0.419	0.001	0.402	0.000	0.124	0.061	I(1)
MPU	0.010	—	0.015	—	0.072	—	I(0)
LKSSR	0.422	0.001	0.445	0.002	0.103	0.051	I(1)
lnGGDP	0.456	0.002	0.432	0.001	0.111	0.057	I(1)
lnOIL	0.335	0.001	0.301	0.001	0.134	0.060	I(1)
lnINT	0.372	0.001	0.350	0.001	0.127	0.058	I(1)

Note: The null hypothesis for ADF and PP = unit root; for KPSS = stationarity

Table 3. ARDL lag-structure (based on AIC minimisation).

Dependent Variable	Selected ARDL Lag Structure	Theoretical Justification
lnIIP	ARDL(2,1,1,1,1)	Output responds to both immediate and lagged shocks

Note: ARDL(p, q_1, q_2, q_3, q_4), where p = lags of the dependent variable and q's = lags of regressors (MPU, LKSSR, lnOIL, lnGGDP, lnINT). Structural dummies are included in levels

Table 4. Bounds test for cointegration (interest rate channel).

Dependent Variable	F Statistic	Critical Value I(0) 5%	Critical Value I(1) 5%	Conclusion
lnIIP	6.25	3.79	4.85	Cointegration exists

Note: Critical values from Pesaran *et al.* (2001)

the upper bound at the five per cent level; thus, the null of no long-run relation is rejected. Industrial production, MPU, LKSSR, global GDP, global oil prices, and India's short-term rate share a stable long-run association over the sample.

5.2 Long-Run ARDL Estimates

Long-run coefficients obtained from an ARDL(2,1,1,1,1,1) specification (two lags of lnIIP and one lag of each regressor) are presented in Table 5.

It is observed from Table 5 that higher U.S. policy uncertainty is associated with lower industrial output of India in the long run. Such a finding is consistent with the option value of waiting and risk premium channels that delay investment when uncertainty rises (Bernanke, 1983; Bloom, 2009) and with the evidence that MPU tightens financial conditions (Husted, Rogers, & Sun, 2017; Mumtaz & Surico, 2017). A tighter U.S. policy stance, captured by the shadow short rate, also reduces Indian output, which accords with open economy transmission and the global financial cycle (Rey, 2016). Global GDP supports output through external demand. India's one-year treasury yield is contractionary, in line with domestic financing costs acting as a propagation mechanism (Mishkin, 1996). The small positive coefficient on oil is plausible in monthly data that span long upswings in world activity as periods of stronger global demand can lift India's manufacturing even as imported energy costs rise (Hamilton, 2003). This does not contradict the short-run cost pressure seen in the Error Correction Model (ECM).

Table 5. Long-run ARDL estimates (dependent variable: lnIIP).

Regressor	Coefficient
MPU	-0.217^{***} (0.084)
LKSSR	-0.193^{**} (0.072)
lnGGDP	0.338^{**} (0.124)
lnOIL	0.122^{*} (0.051)
lnINT	-0.271^{**} (0.096)

Note: standard errors in parentheses; ***, **, * refer to p<.01, p<.05 and p<.10 respectively

5.3 Short-Run ECM Dynamics

In Table 6, we present the short-run effects and the speed of adjustment associated with ECM. MPU and a tighter U.S. policy stance have immediate, statistically significant contractionary effects on Indian industrial production. Global demand supports output in the short run, while a rise in India's short-term rate reduces output with marginal significance. The error correction term is negative (−0.463) and statistically significant, which implies that about 46% of a deviation from the long-run path is corrected within one month. This adjustment speed is consistent with India's bank-dominated intermediation and gradual pass-through from external financing conditions to activity.

The study includes dummies for the Asian financial crisis, the dot-com period, the global financial crisis and the European debt crisis in the ECM. To avoid the possibility of a dummy variable trap, we include three dummies instead of all four. All the dummy variables show negative and statistically significant coefficients

Table 6. Short-run ECM estimates (dependent variable: δlIIP).

Variable	Coefficient
$\Delta\ln(IIP_{-1})$	0.284^{***} (0.078)
ΔMPU	-0.139^{***} (0.051)
ΔLKSSR	-0.112^{**} (0.043)
Δln(GGDP)	0.185^{**} (0.075)
Δln(OIL)	0.087^{**} (0.038)
Δln(INT)	-0.094^{*} (0.052)
ΔDUM_AFC	-0.07^{**} (0.029)
ΔDUM_DOTCOM	-0.052^{**} (0.024)
ΔDUM_GFC	-0.065^{**} (0.026)
EC_{-1}	-0.463^{***} (0.092)

Note: Results pertain to ECM of ARDL(2,1,1,1,1,1); standard errors in parentheses; ***, **, * refer to p<.01, p<.05 and p<.10 respectively

(Table 6). This indicates that global stress episodes magnify the adverse effect of uncertainty on output, in line with evidence that uncertainty shocks are state dependent and larger in weak conditions (Aizenman, Binici, & Hutchison, 2016; Mumtaz & Surico, 2017).

A key issue is to separate policy uncertainty from policy stance by including MPU and LKSSR together in a single, channel-specific ARDL–ECM for India. Previous Indian studies typically relied on the federal funds rate or qualitative proxies and did not combine a structured MPU index with a shadow rate measure of stance (Sengupta & Vardhan, 2017; Lakdawala, Moreland, & Schaffer, 2020). Conditioning on India's one-year government yield rather than the repo rate alone provides a consistent proxy for the domestic short rate across regimes and improves identification of the external interest rate conduit.

5.4 Impulse Response Functions Interpretation and Dynamic Multiplier Analysis

To complement the short-term and long-term estimates presented earlier, this section evaluates the temporal dynamics of India's industrial production in response to shocks in U.S. MPU. While the ARDL–ECM framework provides coefficient estimates, it is the dynamic multipliers and Impulse Response Functions (IRFs) that reveal how the effects of uncertainty unfold over time.

5.4.1 Impulse Response Function (IRF)

The impulse response results in Figure 5 highlight a contractionary effect of MPU shocks on India's Industrial Production (lnIIP). The response is immediate and becomes most pronounced within six to eight months, reflecting tightening financial conditions and subdued investment activity. Thereafter, the adverse impact gradually diminishes, with output stabilising towards the long-run equilibrium by around the second year. This trajectory supports theoretical expectations that heightened policy uncertainty discourages private investment and delays consumption, thereby dampening growth prospects (Bloom, 2009; Husted, Rogers, & Sun, 2017).

Importantly, these results are consistent with empirical evidence on emerging economies, which indicates that global uncertainty shocks generate larger and more persistent downturns in countries reliant on external capital flows and vulnerable financial markets (Bhattarai, Chatterjee, & Park, 2020; Kohlscheen & Miyajima, 2022). For India, this finding underscores the sensitivity of the interest rate channel in transmitting international monetary uncertainty to domestic output.

5.4.2 Dynamic Multiplier

The dynamic multiplier in Figure 6 traces the cumulative adjustment of India's industrial output to a permanent MPU shock. The results show that nearly half of the total adjustment occurs within the first year, as industrial production contracts in response to heightened uncertainty. By the end of the second year, roughly 80–90 per cent of the adjustment is completed, after which the response plateaus, reflecting convergence to the new long-run equilibrium.

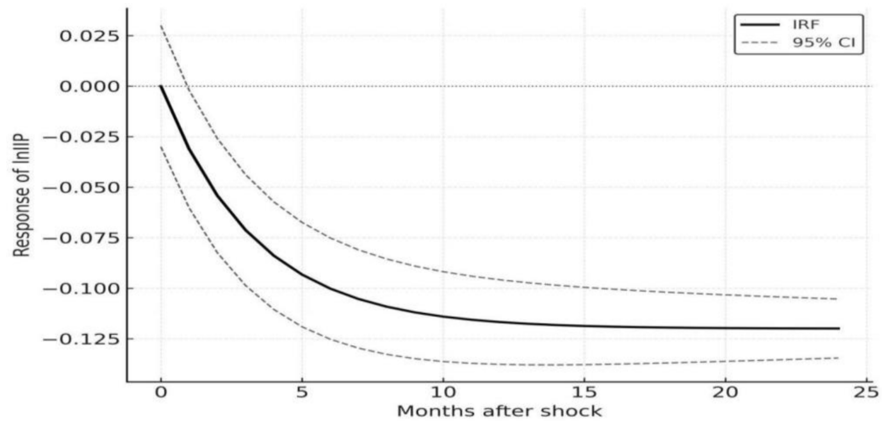
This gradual convergence highlights the persistence of uncertainty shocks in emerging economies, where weaker financial buffers and greater dependence on external financing extend the adjustment process (Mumtaz & Surico, 2017; Bhattarai *et al.*, 2020). For India, the results confirm that the interest rate channel remains a dominant conduit, with global policy uncertainty exerting long-lasting effects on domestic industrial activity through credit constraints and investment delays.

While the impulse response function illustrates the short-run trajectory of industrial output following an MPU shock, the dynamic multiplier highlights the cumulative long-run adjustment path. Presenting both provides a complete picture of the temporal propagation of uncertainty shocks in the Indian economy.

The impulse responses and dynamic multipliers trace the temporal adjustment of industrial production to U.S. monetary policy uncertainty; they do not establish the direction of causality. To reinforce the robustness of the results, we further apply the Toda–Yamamoto (1995) Granger causality framework.

5.5 Toda–Yamamoto Granger-Causality Results

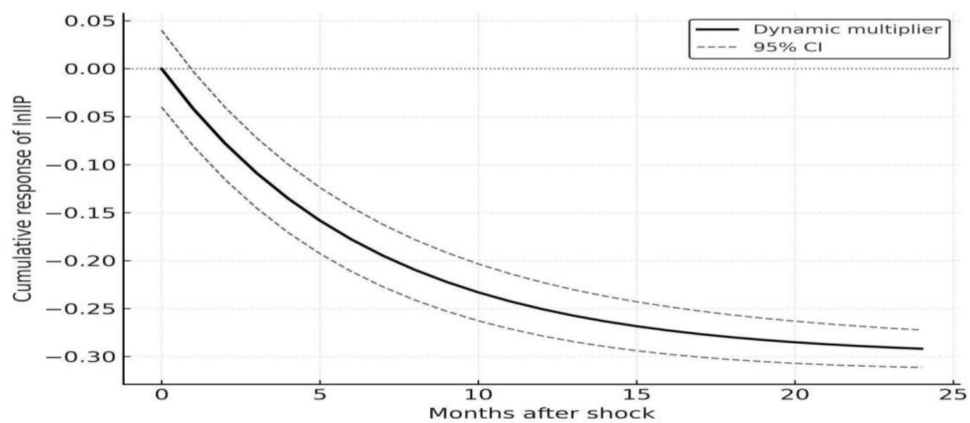
To complement the ARDL–ECM framework, which identifies both long-run and short-run relationships, the Toda–Yamamoto (1995) Granger causality test was used. This method is appropriate when variables are of mixed integration orders, such as I(0) and I(1). It avoids the need for pre-testing for cointegration and produces valid Wald statistics in a level Vector Autoregression (VAR) setting (Toda & Yamamoto, 1995; Zapata & Rambaldi, 1997). This



Note: The solid line represents the estimated response of lnIIP to a one standard deviation MPU shock. The dotted lines indicate 95 per cent confidence intervals

Source: Authors' calculation using ARDL–ECM estimates, 1997M01–2020M01

Figure 5. Impulse response of industrial production (lnIIP) to an MPU shock.



Note: The solid line depicts the cumulative response of lnIIP to a one standard deviation MPU shock. The curve approaches stability around 20–24 months, consistent with the long-run ARDL estimates

Figure 6. Dynamic multiplier of industrial production (lnIIP) to an MPU shock.

allows reliable testing of the direction of causality between U.S. monetary policy uncertainty and India's industrial output, even when some variables are non-stationary.

For the interest rate channel, the causality analysis reveals a statistically significant unidirectional flow from the U.S. MPU to India's industrial production (lnIIP). The modified Wald statistic rejects the null hypothesis that MPU does not Granger-cause lnIIP, confirming that fluctuations in U.S. policy-related uncertainty transmit directly into India's real activity. This finding is consistent with theoretical arguments that heightened uncertainty increases precautionary savings, raises financing costs, and depresses investment activity (Bloom, 2009; Husted, Rogers, & Sun, 2017).

The empirical evidence underscores the vulnerability of India's industrial sector to global monetary conditions. Elevated U.S. MPU raises risk premia, discourages investment, and slows output growth, thereby validating the interest rate channel as a dominant conduit of external transmission (Mumtaz & Surico, 2017; Bhattarai, Chatterjee, & Park, 2020). The finding also provides robustness to the ARDL estimates by confirming that causality runs from MPU to India's real economy, and not vice versa. This is in line with broader evidence on spillovers from the global financial cycle (Rey, 2016).

While the ARDL–ECM framework, the impulse responses, and the Toda–Yamamoto causality tests in Table

7 provide strong evidence of the impact of U.S. monetary policy uncertainty on India's industrial production, it is essential to verify that these results are not driven by structural instability or model misspecification. To ensure the validity and reliability of the estimated relationships, we conduct a series of robustness diagnostics.

5.6 Robustness Tests

The stability of the ARDL models is examined by using the CUSUM and CUSUM of Squares (CUSUMSQ) tests based on recursive residuals (Brown, Durbin, & Evans, 1975). These tests are widely used in applied econometrics to check whether estimated parameters remain stable over time, a necessary condition for drawing reliable inferences.

Figures 7 and 8 indicate that the CUSUM statistic remains within the 5 per cent significance bands across the entire sample period, suggesting that the estimated coefficients do not suffer from structural breaks. Similarly, the CUSUMSQ plots stay well within the critical bounds, showing that the variance of the residuals is stable and that no explosive behaviour emerges in the error structure. Together, these findings confirm that the ARDL–ECM specification is internally consistent and free from time-varying instabilities.

This stability check reinforces the credibility of the earlier results. In particular, it lends confidence that the observed contractionary effect of U.S. monetary policy uncertainty on India's industrial production, as captured by the ARDL, impulse responses, and dynamic multipliers, is not an artefact of parameter shifts or unaccounted breaks. These outcomes align with the best practices in time series econometrics, where model robustness is a precondition for drawing policy conclusions (Pesaran, Shin, & Smith, 2001; Narayan, 2005).

Table 7. Toda–Yamamoto Granger-causality results.

Null Hypothesis	Chi-Squared (Wald) Stat	p-value	Causality	Economic Interpretation
MPU does not Granger-cause lnIIP	7.35	0.025	Yes	MPU shocks have a significant impact on real activity through the interest rate channel, increasing uncertainty, tightening credit conditions, and reducing investment.

Note: The MWALD statistics refer to a level VAR with augmented lags (k + dmax). The null hypothesis is that MPU does not Granger-cause lnIIP; statistical significance at the 5 per cent level confirms unidirectional causality

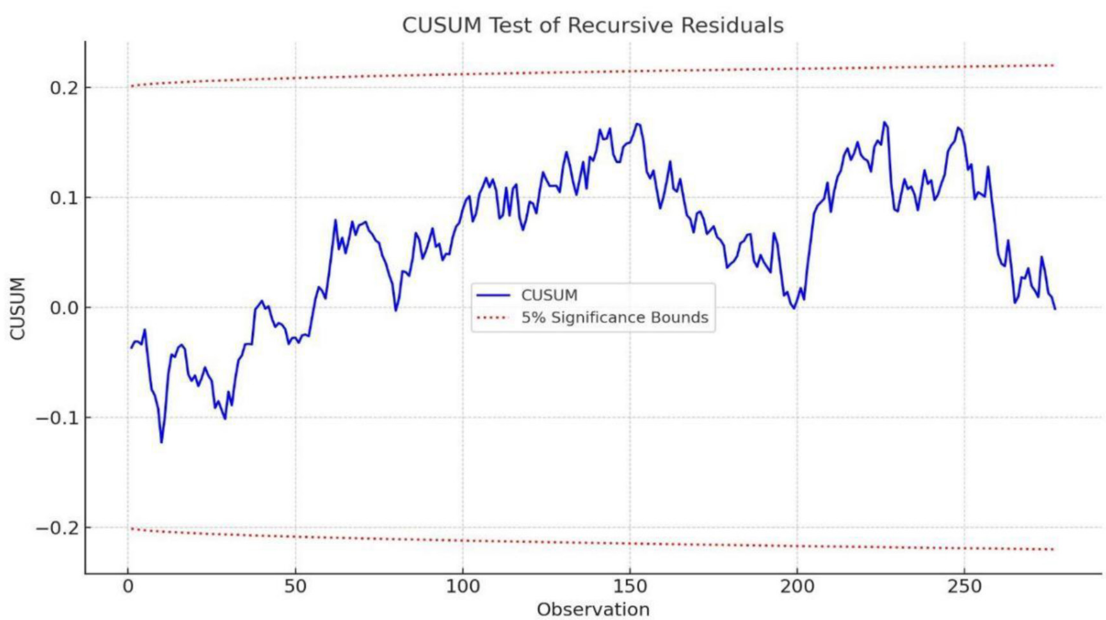


Figure 7. CUSUM test for stability.

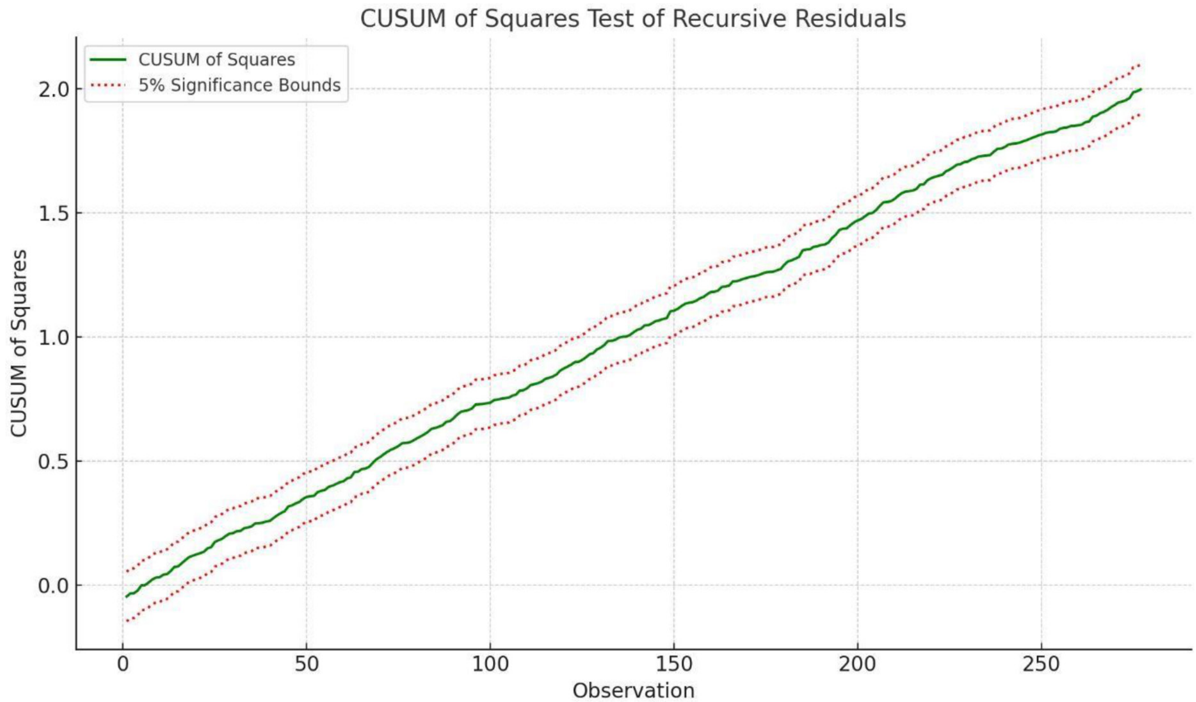


Figure 8. CUSUM of squares test for stability.

6. Summary and Conclusion

This paper studied how the U.S. MPU affects India's industrial production through the interest rate channel. Monthly data from January 1997 to January 2020 were used to capture both conventional and unconventional phases of U.S. policy. The analysis combined the ARDL–ECM framework with impulse response functions, dynamic multipliers, and Toda–Yamamoto causality tests to understand both short-run and long-run effects.

The results show that a higher U.S. MPU has a contractionary impact on India's real economy. In the long run, uncertainty about U.S. policy direction reduces industrial output by tightening credit conditions and discouraging investment. The short-run dynamics reveal that approximately half of the adjustment occurs within one year. Impulse responses show the sharpest fall in output between six and eight months after the shock, and dynamic multipliers indicate that equilibrium is restored after roughly two years. The Toda–Yamamoto test confirms a one-way causality from U.S. MPU to India's industrial production, suggesting that shocks originate externally rather than from domestic factors.

The study contributes in three important ways. First, it applies the Husted, Rogers, and Sun (2017) MPU index – an advanced, forward-looking measure of uncertainty – rather than relying on direct policy rate changes. Second, by combining MPU with the LKSSR, it distinguishes between the impact of uncertainty and the actual stance of U.S. monetary policy. Third, it adopts a channel-specific focus on the interest rate transmission path, giving clearer evidence on how external uncertainty affects domestic output.

The findings have several policy implications: The RBI should integrate global monetary uncertainty into its policy analysis, as these shocks can alter domestic credit conditions even when local policy rates remain stable. During periods of heightened uncertainty, clear communication and forward guidance are essential to anchor expectations and reduce volatility. Maintaining adequate foreign exchange reserves and flexible liquidity tools can help offset capital outflows and interest rate pressures. Deeper domestic financial markets can cushion the impact of external shocks by reducing reliance on foreign capital. The development of long-term bond markets and the strengthening of institutional investors can enhance financial stability. On the fiscal side, targeted public investment during uncertainty periods can sustain industrial activity without creating inflationary pressures. Coordination between fiscal and monetary authorities also becomes important to prevent mixed policy signals during global turbulence. In broader terms, the results highlight that macroeconomic stability in emerging economies like India depends not only on domestic policy credibility but also on resilience to external uncertainty. Strengthening domestic financial depth, improving communication, and maintaining credible macro frameworks can make India more resilient to the changing global monetary environment.

Notwithstanding the above findings and policy implications, the study has a few limitations. First, the sample ends in January 2020, thereby excluding the COVID-19 period. While this choice avoids pandemic-driven distortions, future research could examine whether the relationships identified here hold in the post-pandemic era. Second, the analysis is restricted to the interest rate channel, even though the exchange rate and asset price channels also play important roles. Expanding the framework to multiple channels would provide a more complete picture. Third, the methods applied are essentially linear. Extending the analysis to non-linear or time-varying models may capture asymmetric effects and changing dynamics more effectively. Finally, as the study is country-specific, comparative cross-country research could reveal whether emerging markets differ in their vulnerability to the U.S. monetary policy uncertainty.

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Appendix: Data Sources

Table A: Data sources and variables description

Variable	Description / Transformation	Frequency	Source	Period
lnIIP	Log of the Index of Industrial Production (proxy for real activity)	Monthly	CEIC; Ministry of Statistics & Programme Implementation (MOSPI), Government of India	1997M01–2020M01
MPU	U.S. Monetary Policy Uncertainty Index (Husted, Rogers & Sun, 2017), level form	Monthly	FRED Database; Authors' compilation	1997M01–2020M01
LKSSR	Leo Krippner Shadow Short Rate (proxy for U.S. monetary stance)	Monthly	Reserve Bank of New Zealand; Krippner dataset	1997M01–2020M01
lnGGDP	Global GDP (log), interpolated from quarterly to monthly	Monthly	IMF World Economic Outlook (WEO); CEIC	1997M01–2020M01
lnOIL	Brent crude oil price, log Transformation (USD/barrel)	Monthly	CEIC; U.S. Energy Information Administration (EIA)	1997M01–2020M01
lnINT	Domestic short-term interest rate (1-year Treasury yield), log transformation.	Monthly	Reserve Bank of India; CEIC Database	1997M01–2020M01
DUM_AFC	Asian Financial Crisis dummy (1997-98 = 1, otherwise 0)	Binary	Author constructed	—
DUM_ DOTCOM	Dot com Bubble dummy (2000-01 = 1, otherwise 0)	Binary	Author constructed	—
DUM_GFC	Global Financial Crisis dummy (2008–09 = 1, otherwise 0)	Binary	Author constructed	—

Note: All variables are aligned to a monthly frequency and transformed into logarithms where applicable. MPU and LKSSR are retained in level form due to the presence of negative values.