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Monetary policy shocks and multi-scale positive and negative bubbles in an emerging country: the case of India

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Abstract

We employ the Multi-Scale Log-Periodic Power Law Singularity Confidence Indicator (MS-LPPLS-CI) approach to identify positive and negative bubbles in the short-, medium, and long-term for the Indian stock market, using weekly data from November 2003 to December 2020. We use a nonparametric causality-in-quantiles approach to analyze the predictive impact of monetary policy shocks on bubble indicators. We find, in general, strong evidence of predictability across the entire conditional distribution for the two monetary policy shock factors, with stronger impacts for negative bubbles. Our findings have critical implications for the Reserve Bank of India, academics, and investors.

Keywords: Multi-scale positive and negative bubbles, Monetary policy shocks, Nonparametric causality-in-quantiles test, India

JEL Classification: C22, E52, G10

Introduction

According to the discounted cash flow model, stock prices are equal to the present value of expected future net cash flows. While providing a detailed literature review, Bernanke and Kuttner (2005), Maio (2014), and more recently Cepni and Gupta (2021) and Cepni et al. (2021), have highlighted that monetary policy shocks can affect stock prices by altering investors' expectations about future cash flows related to economic activity and influencing the cost of capital, i.e., the real interest rate used to discount future cash flows and/or the risk premium associated with holding stocks. Importantly, a more restrictive monetary policy usually implies higher discount rates and lower future cash flows; therefore, these two channels are interconnected. Consequently, contractionary monetary policy shocks should correlate with lower stock prices owing to higher discount rates for the expected cash flow stream and/or reduced future economic activity. By contrast, expansionary monetary policy shocks are often seen as positive news because they are usually associated with low interest rates, increased economic activity, and higher earnings for firms in the economy, resulting in higher stock prices.

However, Galí (2014) recently challenged the conventional view connecting interest rates with asset prices and their bubbles. This is because, in equilibrium, the case of rational asset price bubbles implies that the bubble component must grow at the interest rate, and as such, the bubble may be enlarged with an interest rate increase. Furthermore, as suggested by the theory of rational bubbles, the relative size of the bubble component should dictate the effects of monetary policy on asset prices. That is, when the bubble component is small (large) compared to the fundamental, an increase in the interest rate should negatively (positively) impact the price of an asset. This occurs because, during "normal" (i.e., the bubble is small compared to the fundamental) times, an interest rate increase always reduces the "fundamental" price of the asset, which is the dominant effect. However, if the relative size of the bubble is large, the positive effect on the bubble outweighs the negative impact on the fundamental component in the event of an interest rate. However, a study by Miao et al. (2019) has shown that the unexpected theoretical results in Galí (2014) are due to the choice of a particular equilibrium solution from the multiple equilibria in the model. Miao et al. (2019) have focused on the forward-looking minimal state variable solution corresponding to an unstable bubbly steady state, which in turn leads to a negative response of stock prices to a monetary policy shock; their results are consistent with conventional views. These findings are further confirmed by Dong et al. (2020), who introduce bubbles into a Dynamic Stochastic General Equilibrium (DSGE) model with heterogeneous entrepreneurs.

Theoretically, the role of monetary policies in containing predictive information for stock market bubbles is well established through various channels. However, the effect could be either positive or negative (depending on the size of the bubble), with the former being more likely, thus ensuring that a lack of predictability with the cancellation of the effects of opposite signs with equal magnitudes is less likely. A substantial body of literature has focused on the impact of conventional and unconventional monetary policies (interest rates) on stock market bubbles, associated with deviation of stock price from its fundamental value, as captured by dividends,[1] particularly for developed economies (see, for example, Galí and Gambetti (2015), Caraiani and Călin (2018), Pan (2020), Caraiani et al. (2023), van Eyden et al. (2023), and references cited therein).[2]

We aim to extend this line of research in the context of an emerging country, India, by analyzing the effect of monetary policy shocks on stock market bubbles over the weekly period from November 2003 to December 2020. The choice of India is motivated by two reasons. First, it is now theoretically accepted that bursting bubbles can lead to protracted recessions and substantial economic losses (Biswas et al. 2020).[3] Additionally, India—along with China among emerging markets—is highly integrated with the global financial system (Lakdawala 2021; Pan and Mishra 2022). Therefore, the collapse of the Indian stock market is likely to have negative international spillover effects on both financial and economic activities. Naturally, a detailed analysis of the role of monetary policies in impacting the boom-bust cycle of the Indian stock market is of

[1] In this regard, refer to the theoretical works of Important contributions include those of Blanchard (1979), Blanchard and Watson (1982), and Flood and Garber (1980).

[2] Gupta et al. (2023) analysed the effect of US monetary policy shocks on the bubbles of the BRICS (Brazil, Russia, India, China and South Africa) bloc, and detected limited impact.

[3] Empirical evidence in this context can be found in the works of Reinhart and Rogoff (2009) and Jordà et al. (2015).

paramount importance (Rajan 2015), providing the first motivation to consider India as a case study in the context of the nexus between monetary policy and equity bubbles. Second, and more importantly, we choose India owing to the availability of reliable, relatively long-span, high-frequency, publicly available data on monetary policy shocks, as recently developed by Lakdawala and Sengupta (2024). These authors synthesize high-frequency financial market data with a narrative analysis of central bank communication and related media coverage. As noted by Nakamura and Steinsson (2018a, b), the use of high-frequency data enables them to identify daily monetary policy surprises "in a relatively cleaner manner," allowing monetary policy announcements to capture the effect on agents' beliefs about economic fundamentals beyond monetary policy via the "information channel." Understandably, a high-frequency analysis of bubble detection and the associated predictive impact of monetary policy is of paramount importance to policymakers as boom-bust cycles in stock markets are likely to be informative about the future path of low-frequency macroeconomic variables considering the information being fed into mixed data sampling (MIDAS) models for nowcasting (Bańbura et al. 2011).

In terms of bubble detection, we employ the Log-Periodic Power Law Singularity (LPPLS) model introduced by Johansen et al. (1999) and improved by Johansen et al. (2000), and Sornette (2003). The LPPLS model allows us to detect both positive bubbles, which are upward-accelerating prices followed by a crash, and negative bubbles, which are the opposite. Subsequently, we characterized the bubbles (positive and negative) into three time scales (short-, medium-, and long-term) by applying the multi-scale LPPLS confidence indicators (CI) by Demirer et al. (2019). The time scales correspond to trading activities over one to three months (short-term), three months to a year (medium-term), and one year to two years (long-term). It is worth noting that the LPPLS-CI model is the only one that allows us to identify both positive and negative multi-scale bubbles, as Balcilar et al. (2016), Zhang et al. (2016), Sornette et al. (2018), and Nielsen et al. (2024) have shown in their respective reviews of the literature.[4] This is an important characteristic of the LPPLS-CI model as it allows us to account for potential asymmetries in the response of the Indian equity stock market bubbles to monetary policy shocks. This is because crashes and recoveries at different horizons can convey different information to market participants, as suggested by the Heterogeneous Market Hypothesis (HMH; Müller et al. 1997).[5]

After obtaining the six stock market bubble indicators for India, we analyze the predictive impact of monetary policy shocks on each bubble category using the nonparametric causality-in-quantiles test proposed by Jeong et al. (2012). This test enables us to detect predictability across all conditional distributions of the LPPLS-CIs resulting from monetary policy shocks while simultaneously controlling for misspecification owing to uncaptured nonlinearity and structural breaks in these relationships, for which we provide statistical evidence. Given the presence of fat tails in the unconditional distributions

[4] Generally tests to detect only positive and time scale independent bubbles based on the popular generalized supremum augmented Dickey-Fuller (GSADF) approach developed by Phillips et al. (2015a, b) (see, for example, the detailed discussions in Khan et al. (2021) and Khan (2023)).

[5] The HMH states that different classes of market agents namely, investors, speculators and traders, populate asset markets and differ in their sensitivity to information flows at different time horizons.

of the LPPLS-CIs, a quantile-based nonparametric predictive approach is more relevant in our context. This approach simultaneously controls for misspecification due to nonlinearity and regime changes, compared to conditional mean-reliant nonlinear and/or nonparametric causality tests [see, for example, Hiemstra and Jones (1994), Diks and Panchenko (2005, 2006), and Nishiyama et al. (2011)]. Our test is a more elaborate procedure for detecting causality at each point of the bubble indicators, capturing the existence or nonexistence of predictability owing to monetary policy shocks at various sizes of the LPPLS-CIs. This makes the test inherently time-varying in nature. As a more general test, our method is more likely to identify causality at specific quantiles when conditional mean-based tests may fail. Additionally, our tests do not suffer from misspecification as we do not specify and test for the optimal number of regimes. Instead, we can test for predictability at each point of the conditional distribution characterizing specific bubble regimes and do not need to determine the number of regimes as in Markov-switching models of causality (Ben Nasr et al. 2015; Balcilar et al. 2018a, b).

Although some studies have examined the role—albeit weak—of Indian monetary policy shocks on its stock prices and/or returns [see, for example, Bhattacharyya and Sensarma (2008), Pal and Mittal (2011), Singh and Pattanaik (2012), Prabhu et al. (2016, 2020), Khuntia and Hiremath (2019), and Lakdawala and Sengupta (2024), among others], to the best of our knowledge, this is the first paper to analyze the high-frequency predictive impact of monetary policy shocks on multi-scale positive and negative bubbles using a nonparametric quantiles-in-causality approach. It should be noted that, although we use the monetary policy innovations data of Lakdawala and Sengupta (2024), the abovementioned authors have studied the heterogeneous impact of these innovations on bond and stock markets across governor regimes, which is markedly different from the objectives of our work.

The remainder of the paper is organized as follows: Section "Methodologies" outlines the methodologies associated with the detection of bubbles and the nonparametric causality-in-quantiles test. Section "Data" is devoted to discussing the data. Section "Empirical Findings" presents the empirical results, and Section "Conclusion" concludes the paper.

Methodologies

Estimating the multi-scale log-periodic power law singularity (LPPLS) model[6]

In this subsection, we discuss the econometric framework used to detect our multi-scale positive and negative bubble indicators. Using the LPPLS model given below, we adopt the stable and robust calibration scheme developed by Filimonov and Sornette (2013):

$$\ln E[p(t)] = A + B(t_c - t)^m + C(t_c - t)^m \cos\left(\omega \ln (t_c - t)^m - \phi\right) \tag{1}$$

The termination date of the bubble (i.e., the critical time) is represented by the parameter t_c; it signifies a transition into a new market regime, which can be viewed as a change in the underlying market dynamics or the beginning of a different market phase. The expected log value of the observed time series (i.e., the stock price-dividend ratio at time

[6] The discussion of the MS-LPPLS-CIs approach draws heavily from Demirer et al. (2019), Caraiani et al. (2023), Gupta et al. (2023), and van Eyden et al. (2023).

t_c) is represented by A. This parameter is pivotal as it provides an estimation of the highest price level on a logarithmic scale when the bubble is at its maximum. The amplitude of the power law acceleration, B, indicates the bubble's rate of growth, with a larger value typically indicating a steeper price ascent. C represents the amplitude of the log-periodic oscillations. These oscillations represent the cyclical behavior often observed in bubble dynamics. A higher amplitude suggests more pronounced price oscillations around the bubble's main growth trajectory. The degree of super-exponential growth, m, is a clear indicator of how rapidly the bubble is inflating. While its importance might be obvious, it is critical in determining the explosive nature of the bubble. The scaling ratio of the temporal hierarchy of oscillations (i.e., ω) provides insight into the relative spacing between successive oscillations. This can help in determining patterns and predicting future oscillations. Finally, ϕ denotes the time scale of the oscillations and gives a sense of the duration over which these cyclical behaviors persist.

As in Filimonov and Sornette (2013), we reformulate Eq. (1) by eliminating the nonlinear parameter ϕ and expanding the linear parameter C to be $C_1 = C\cos\phi$ and $C_2 = C\cos\phi$, to reduce the complexity of the calibration process.

The new formulation can be written as

$$\ln E[p(t)] = A + B\big(f\big) + C_1\big(g\big) + C_2(h) \tag{2}$$

where

$$\begin{aligned} f &= (t_c - t)^m \\ g &= (t_c - t)^m \cos[\omega \ln (t_C - t)] \\ h &= (t_c - t)^m \sin[\omega \ln (t_c - t)] \end{aligned}$$

We fit Eq. (2) to the log of the price-dividend ratio to estimate the three nonlinear parameters $\{t_c, m, \omega\}$ and four linear parameters $\{A, B, C_1, C_2\}$. To achieve this, we use the L^2 norm to obtain the sum of squared residuals, given by the following:

$$F(t_c, m, \omega, A, B, C_1, C_2) = \sum_{i=1}^{N} \left[\ln p(\tau_i) - A - B\big(f_i\big) - C_1\big(g_i\big) - C_{2(h_i)}\right]^2 \tag{3}$$

As the estimation of the three nonlinear parameters depends on the four linear parameters, we obtain the following cost function:

$$F(t_c, m, \omega) = \min_{A,B,C_1,C_2} F(t_c, m, \omega, A, B, C_1, C_2) = F\left(t_c, m, \omega, \hat{A}, \hat{B}, \hat{C}_1, \hat{C}_2\right) \tag{4}$$

We estimate the four linear parameters by solving the optimization problem:

$$\left\{\hat{A}, \hat{B}, \hat{C}_1, \hat{C}_2\right\} = \arg \min_{A,B,C_1,C_2} F(t_c, m, \omega, A, B, C_1, C_2) \tag{5}$$

which can be done analytically by solving the following matrix equation:

$$\begin{pmatrix} N & \sum f_i & \sum g_i & \sum h_i \\ \sum f_i & \sum f_i^2 & \sum f_i g_i & \sum f_i h_i \\ \sum g_i & \sum f_i g_i & \sum g_i^2 & \sum g_i h_i \\ \sum h_i & \sum f_i h_i & \sum g_i h_i & \sum h_i^2 \end{pmatrix} \begin{pmatrix} \hat{A} \\ \hat{B} \\ \hat{C}_1 \\ \hat{C}_2 \end{pmatrix} = \begin{pmatrix} \sum \ln p_i \\ \sum \mathrm{f_i} \ln p_i \\ \sum \mathrm{g_i} \ln p_i \\ \sum \mathrm{h_i} \ln p_i \end{pmatrix} \tag{6}$$

Next, we determine the three nonlinear parameters by solving the following nonlinear optimization problem:

$$\left\{\hat{t}_c, \hat{m}, \hat{\omega}\right\} = \arg \min_{t_c, m, \omega} F(t_c, m, \omega) \tag{7}$$

We use the Sequential Least Squares Programming (SLSQP) search algorithm (Kraft 1988) to find the best estimation of the three nonlinear parameters $\{t_c, m, \omega\}$.

The sensitivity of bubble patterns in the log price-dividend ratio time series is measured by the LPPLS confidence indicator, as in Sornette et al. (2015). The smaller (larger) the LPPLS confidence indicator (CI), the less (more) reliable the LPPLS bubble pattern. To calculate this, we calibrate the LPPLS model to shrinking time windows. That is, we shift t_1 (the initial observation) dt steps forward in time toward t_2 (the final observation) for each fit of the LPPLS model. For each of these fits, we filter the estimated parameters against established thresholds, and the qualified fits are taken as a fraction of the total number of positive or negative fits. A positive fit has estimated $B < 0$, and a negative fit has estimated $B > 0$, yielding the positive and negative bubble indicators, respectively.

After getting the positive and negative bubble indicators, we incorporate bubbles of varying multiple time scales into this analysis, as in the work of Demirer et al. (2019). To achieve this, we sample the time series in steps of five trading days and then create the nested windows $[t_1, t_2]$ and iterate through each window in steps of two trading days. As such, we obtain a weekly resolution, based on which we construct the following indicators:

- Short-term bubble: A number $\in [0, 1]$ that denotes the fraction of qualified fits for estimation windows of length $dt := t_2 - t_1 \in [30 : 90]$ trading days per t_2. This indicator comprises $(90 - 30)/2 = 30$ fits.
- Medium-term bubble: A number $\in [0, 1]$ that denotes the fraction of qualified fits for estimation windows of length $dt := t_2 - t_1 \in [30 : 90]$ trading days per t_2. This indicator comprises $(300 - 90)/2 = 105$ fits.
- Long-term bubble: A number $\in [0,\ 1]$ that denotes the fraction of qualified fits for estimation windows of length $dt := t_2 - t_1 \in [30 : 90]$ trading days per t_2. This indicator comprises $(745 - 300)/2 = 223$ fits.
- Filter conditions: After calibrating the model, the following filter conditions, as described by Filimonov and Sornette (2013) and Demirer et al. (2019), are applied to determine which fits are qualified:

  $$m \in [0.01, 0.99]$$

  $$\omega \in [2, 15]$$

  $$t_c \in [max(t_2 - 60, t_2 - 0.5(t_2 - t_1)), min(252, t_2 + 0.5(t_2 - t_1))]$$

$$O > 2.5$$

$$D > 0.5$$

where $O = \frac{\omega}{2\pi} \ln \left(\frac{t_c - t_1}{t_c - t_2} \right)$ is the number of oscillations, and $D = \frac{m|B|}{\omega|C|}$ captures the damping parameter required to ensure that the crash hazard rate, *h(t)*, is non-negative. In sum, the filter conditions are essential criteria that aid in the identification and study of bubbles. While m is indicative of the growth rate and hence a direct measure, other parameters such as B, C, ω, and ϕ might be less intuitive. They help in understanding the bubble's nuanced dynamics. For instance, while B gives a sense of the overall growth rate, C offers insights into the fluctuations around this rate. Similarly, ω and ϕ together help in predicting the periodic nature and possible repetition of these fluctuations, allowing for a deeper understanding and possibly early identification of bubble dynamics.

Nonparametric causality-in-quantiles test

In this subsection, we briefly present the methodology for testing nonparametric quantiles-based causality as developed by Jeong et al. (2012).[7] Let y_t denote a specific LLPLS-CI and x_t the relevant monetary policy shock. Further, let $\mathrm{Y}_{t-1} \equiv (y_{t-1}, \ldots, y_{t-p})$, $X_{t-1} \equiv \left(x_{t-1}, \ldots, x_{t-p}\right)$, $Z_t = (X_t, Y_t)$, and $F_{y_t|\cdot}(y_t|\bullet)$ denote the conditional distribution of $\mathrm{y_t}$ given.

Defining $Q_\theta(Z_{t-1}) \equiv Q_\theta\left(y_t|Z_{t-1}\right)$ and $Q_\theta(Y_{t-1}) \equiv Q_\theta\left(y_t|Y_{t-1}\right)$, we have $\mathrm{F}_{\mathrm{y_t}|\mathrm{Z_{t-1}}}\left\{\mathrm{Q}_\theta(\mathrm{Z_{t-1}})|\mathrm{Z_{t-1}}\right\} = \theta$ with probability one. The (non)causality in the θ-th quantile hypotheses to be tested are

$$H_0 : P\left\{F_{y_t|Z_{t-1}}\{Q_\theta(Y_{t-1})|Z_{t-1}\} = \theta\right\} = 1 \tag{8}$$

$$H_1 : P\left\{F_{y_t|Z_{t-1}}\{Q_\theta(Y_{t-1})|Z_{t-1}\} = \theta\right\} < 1 \tag{9}$$

Jeong et al. (2012) show that the feasible kernel-based test statistics have the following format:

$$\hat{J}_T = \frac{1}{T(T-1)h^{2p}} \sum_{t=p+1}^{T} \sum_{s=p+1, s\neq t}^{T} K\left(\frac{Z_{t-1} - Z_{s-1}}{h}\right) \hat{\varepsilon}_t \hat{\varepsilon}_s \tag{10}$$

where $\mathrm{K}(\cdot)$ is the kernel function with bandwidth h; T is the sample size; p is the lag order, and $\hat{\varepsilon}_t = 1\{y_t \leq \hat{Q}_\theta(Y_{t-1})\} - \theta$ is the regression error, where $\hat{Q}_\theta(Y_{t-1})$ is an estimate of the θ-th conditional quantile, and $1\{\bullet\}$. is the indicator function. The *Nadarya-Watson* kernel estimator of $\hat{Q}_\theta(Y_{t-1})$ is given by

$$\hat{Q}_\theta(Y_{t-1}) = \frac{\sum_{s=p+1, s\neq t}^{T} L\left(\frac{Y_{t-1} - Y_{s-1}}{h}\right) 1\{y_s \leq y_t\}}{\sum_{s=p+1, s\neq t}^{T} L\left(\frac{Y_{t-1} - Y_{s-1}}{h}\right)} \tag{11}$$

[7] Our presentation relies on expositions of the the nonparametric quantiles-based causality test in several prominent recent papers, for example, Balcilar et al. (2017, 2018b, 2021), Gkillas et al. (2019, 2021), among others.

with $L(\bullet)$ denoting the kernel function.

Three key parameters need to be specified to empirically implement a causality test via quantiles. First, bandwidth (h), which we use in the leave-one-out least-squares cross-validation. Second, lag order (p), which is set based on the Schwartz Information Criterion (SIC). Last, for the kernel types for $K(\cdot)$ and $L(\cdot)$, we use Gaussian kernels.

Data

The bubble indicators

We derive the six weekly bubble indicators (positive and negative bubbles at short-, medium-, and long-term time scales) for India based on the natural logarithms of price-dividend ratio, at a daily frequency, and we obtain both individual series from Refinitiv Datastream (in the local currency). As the dividend-price (the use of which is in line with the literature) ratio is free from any unit of measurement, it is also unaffected by exchange rate movements. Each of the six derived multi-scale LPPLS-CI values for India, as derived from the econometric model discussed in Section "Estimating the Multi-Scale Log-Periodic Power Law Singularity (LPPLS) Model", is sampled at a weekly frequency, as shown below in Fig. 1. For computational efficiency, while the underlying dataset we utilize for calibration includes the daily logarithmic values of the price-dividend data, we advance our calibration window in five-day increments. We made this choice following the methodology introduced by Demirer et al. (2019) to ease computational demands, while still capturing the relevant dynamics of the financial market. In other words, the MS-LPPLS-CIs are available weekly. This, we believe, is not a concern as, in any event, the monetary policy shocks data utilized by us and discussed in detail below are basically available for only one particular day and associated with the meeting dates of the central bank during a specific week; hence, this does not require any averaging across multiple dates in a week.

The green, purple, and red lines represent the short-, medium-, and long-term indicators, respectively, while the black line gives the log price-to-dividend ratio in Fig. 1. Higher LPPLS-CI values for a particular time scale indicate that the LPPLS signature is present for many of the fitting windows to which the model was calibrated, making it more reliable.

We observe two prominent long-term positive LPPLS-CI regimes. The first precedes the global financial crisis (GFC), consistent with Chang et al. (2016), and the second appears in 2015, 2016, 2018, and 2020. The latter set mainly occurs during periods of Chinese stock market turbulence, Brexit, monetary (demonetization) and fiscal policy (introduction of long-term capital gains taxes), and the outbreak of the COVID-19 pandemic. The long-term negative LPPLS-CI values are notably fewer, with the most evident negative bubble for this scale happening after the GFC and particularly in 2012, capturing the recovery primarily driven by higher inflows from foreign institutional investors given the relatively higher interest rates in emerging markets, while developed countries were still struggling owing to the European sovereign debt crisis. We see pronounced LPPLS-CI values for both positive and negative bubbles wherever we observe spikes in the long-term indicators. Additionally, we notice strong positive short- and

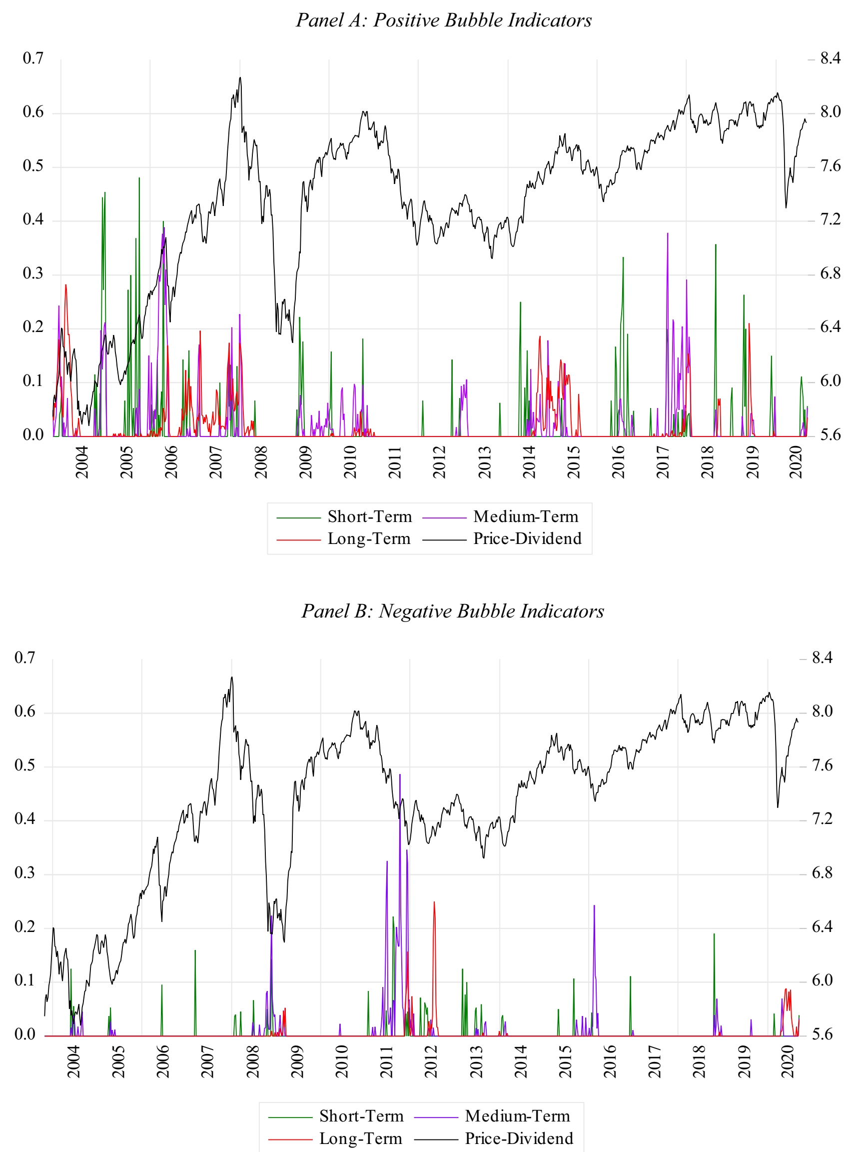

Fig. 1 Bubble Indicators and log of price-dividend ratio. Panel **A**: positive bubble indicators. Panel **B**: negative bubble indicators

medium-term LPPLS-CI values emerging before the robust long-term LPPLS-CI values leading up to the GFC.

In general, long-term scales produce fewer signals but seem to detect larger crashes or rallies, whereas smaller scales generate more signals that precede smaller crashes or rallies. Overall, the empirical findings support the assertion that the LPPLS framework is a versatile tool for identifying bubbles across various time scales. Additionally, both positive and negative bubble indicators at the three scales appear to convey unique information and may be influenced differently by Indian monetary policy shocks, as represented by the target and path factors.

Monetary policy shocks

With regard to the metrics of monetary policy shocks, we rely on the recent work by Lakdawala and Sengupta (2024) in this context.[8] More specifically, these authors combine high-frequency financial market data with a narrative analysis of official central bank statements and related media discussions. In particular, Lakdawala and Sengupta (2024) use changes in the Overnight Index Swap (OIS) rates within a narrow window surrounding the Reserve Bank of India (RBI)'s monetary policy announcements, which in turn captures the unexpected (or surprise) component.[9] Furthermore, by utilizing OIS rates of various maturities (1, 3, 6, 9 months and 1 year), Lakdawala and Sengupta (2024) capture any potential information obtained by the market regarding the future path of the policy rate from RBI communication.

Technically speaking, Lakdawala and Sengupta (2024) conducted a principal components analysis of the OIS rate changes across five maturities over 115 announcement dates. The first two principal components together accounted for almost 97% of the variation in OIS rate changes on RBI announcement days. However, no economic meaning can be derived from these principal components as they are correlated with both the short- and long-end of the OIS rate curve. To overcome this, Lakdawala and Sengupta (2024) provided a structural interpretation, that is, they transformed these into the so-called "target" and "path" factors, following Gürkaynak et al. (2005). The target factor captures surprise (or unexpected) changes to the reserve bank's short-term policy rate target, while the path factor contains information on unexpected changes to forward guidance. In other words, the path factor captures any surprise news that results in the markets changing their expected path for future policy rates. Just like the principal components, these two factors are constructed to be orthogonal to one another, which ensures that the path factor captures news about future rates uncorrelated to surprise changes in the contemporaneous policy target rate. This is achieved using a factor-rotating methodology, as described in detail in Lakdawala and Sengupta (2024). The path and target factors are depicted in Fig. 2.

Lakdawala and Sengupta (2024) used narrative analysis to confirm the reliability of the OIS rates—and thus of the two factors—in capturing revisions of market expectations in response to RBI decisions. To this end, the authors examined the official monetary policy statements of the RBI, along with an analysis of the Indian financial media's reaction to these announcements. Considering the dates associated with substantial changes in the factors, Lakdawala and Sengupta (2024) concluded that the factors capture surprises aligning with their interpretation of the RBI decisions, the language used in the statements, and the corresponding media discussion.

Based on the availability of data of the monetary policy shocks, our analysis covers the weekly period of November 3, 2003 (first week) to December 4, 2020 (first week), for 882 observations. It is important to note that the path and target factors have values of zero on non-announcement days. The data are summarized in Table 1, and as observed, the

[8] The data are available publicly from the data-segment of the website of Professor Aeimit Lakdawala at: https://aeimit.weebly.com/data.html.

[9] The RBI uses multiple tools such as, the repo rate, the reverse repo rate, the bank rate and the cash reserve ratio, to conduct monetary policy. Hence, tracking OIS rates allows one to capture changes in short-term funding conditions regardless of the central bank tool(s).

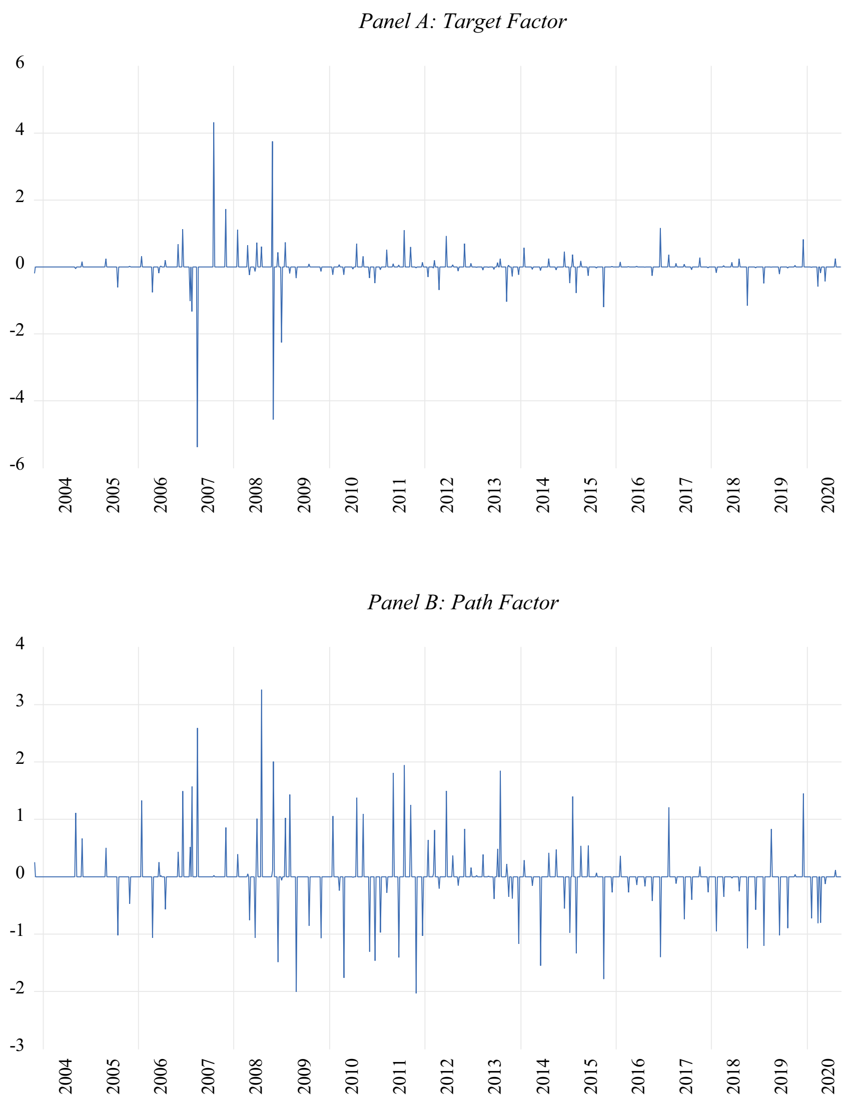

Fig. 2 Monetary policy shocks

bubble indicators (as well as the monetary policy shocks) are non-normal. This provides an initial motivation for our quantiles-based causality framework.

To gain an initial understanding of the correlation between bubble indicators and monetary policy shocks, we refer to Fig. 3, which displays the conditional quantiles-based response of the bubble indicators stemming from various quantiles of the monetary policy shocks. This is derived from the Quantiles-on-Quantiles (QQ) regression by Sim and Zhou (2015). The technical details of this method can be found in Appendix A. As observed, the effect of the target and path factors on the negative bubble indicators is generally positive, while for the positive bubble indicators, the effect is negative, with limited variation across the quantiles of the monetary policy shocks. These observations align with traditional intuition, unlike that of Galí (2014), as contractionary (expansionary) monetary policy tends to result in a decline (increase) in stock returns and cause negative bubble indicators to increase (decrease) in value. Conversely, positive

Table 1 Summary statistics

Statistic	Positive short-term	Positive medium-term	Positive long-term	Negative short-term	Negative medium-term	Negative long-term	Target factor	Path factor
Mean	0.016	0.019	0.015	0.003	0.008	0.003	0	0.002
Median	0	0	0	0	0	0	0	0
Maximum	0.481	0.389	0.283	0.222	0.487	0.25	4.321	3.259
Minimum	0	0	0	0	0	0	− 5.38	− 2.034
Std. Dev	0.055	0.052	0.039	0.019	0.036	0.017	0.36	0.358
Skewness	4.936	3.962	3.259	7.151	7.609	9.611	− 3.009	1.225
Kurtosis	31.391	20.78	14.735	62.789	73.593	113.596	127.192	24.879
Jarque–Bera	33,204***	13,925***	6622***	138,887***	191,651***	463,081***	568,152***	17,812***
Observations	882	882	882	882	882	882	882	882

Std. Dev. stands for standard deviation; the null hypotheses of the Jarque–Bera test correspond to the null of normality

*** indicates rejection of the null hypothesis at a 1% level of significance

bubble indicators are likely to decrease (increase) in value as they capture rapidly declining stock prices before recovery and accelerating prices before a crash. In line with Galí (2014), however, we observe some degree of variation in the impact at high quantiles of the MS-LPPLS-CIs and the two factors of monetary policy shocks.

Empirical findings

To compare the strength of predictability between the two monetary policy shocks and the short-, medium-, and long-term positive and negative bubble indicators, we standardize the target and path factors as well as the six LPPLS-CIs by dividing them by their corresponding full-sample standard deviations.

We draw the following observations from the predictive analyses:

(a) For the sake of completeness and comparability with the nonparametric causality-in-quantiles framework, we conduct the linear Granger causality test as shown in Table 2. As evident, we find no indication of predictability running from the target and path factors to the six bubble indicators. This finding appears to align with the weak effect of Indian monetary policy on its stock prices and/or returns, as reported in earlier literature, which also primarily relies on linear models.

(b) With the linear specification showing no evidence of causality, we next examine whether these results could be due to misspecification. The presence of structural breaks and, more specifically, non-linearity in the error terms would indicate this. As such, we first test for the presence of nonlinearity in the relationship between the six LPPLS-CIs and the two monetary policy shocks using Brock et al. (1996, BDS) test on the residuals from the linear model used in the linear Granger causality tests. The BDS test tests the null hypothesis of *i.i.d.* residuals at various dimensions (m) against the alternative of non-*i.i.d.* residuals. The results are presented in Table 3, where we find that the BDS test yields overwhelming evidence of nonlinearity (i.e., the null hypothesis of linearity [*i.i.d.* residuals] is rejected at the highest level of significance). This result is consistent across all 12 predictive cases consid-

Table 2 Linear granger causality test results

Predictor	Positive short-term	Positive medium-term	Positive long-term	Negative short-term	Negative medium-term	Negative long-term
Target factor	0.039	0.785	0.039	0.003	0.051	0.010
Path factor	0.102	0.046	1.171	1.178	0.321	0.498

Entries correspond to $\chi^2(1)$ test statistic of the null hypothesis of no Granger causality

ered. In sum, the BDS test confirms that the linear model is indeed misspecified owing to the existence of uncaptured nonlinearity; hence, further predictive inference must rely on a nonlinear model, which happens to be our nonparametric causality-in-quantiles approach.

(c) Next, we address the issue of instability in the linear model and potential misspecification by examining the presence of possible structural breaks in the relationship between monetary policy shocks and stock market bubbles in India. For this purpose, we utilize the *Max-F*, *Ave-F*, and *Exp-F* tests for parameter instability arising owing to structural breaks, as developed by Andrews (1993). These tests have the null hypothesis of parameter constancy against the alternative of parameter instability. The *Max-F* test is used to analyze whether a swift regime shift has occurred, whilst the *Ave-F* and *Exp-F* tests determine whether the model is stable over time. Based on the results reported in Table 4, we find widespread evidence of regime changes, with the strongest results of parameter instability derived under the *Max-F* test. As the parameter estimates are indeed unstable over the full sample period, we conclude that our linear Granger causality results are invalid. To achieve accurate causal analysis in our context, we must rely on an econometric model that is inherently time-varying, which we accomplish through our quantiles-based nonlinear setup.

(d) In light of the presence of nonlinearity and regime changes in the relationship between the target and path factors and the six LPPLS-CIs, our linear Granger causality results are clearly unreliable. This provides strong statistical motivation to utilize the nonparametric causality-in-quantiles testing method, which can accommodate such misspecifications. Now, examining the standard normal test statistics derived from the quantiles-based results in Table 5, over the range of 0.10–0.90, we draw the following important conclusions:

(e) Unlike the linear Granger causality findings, the quantiles-based model detects strong evidence of predictability from both the target and path factors over the entire quantile limit considered under the multi-scale negative bubbles indicators and also for the positive LPPLS-CIs, barring the highest considered quantile of 0.90. When we compare the values of the test statistics, we find that the predictive impact is stronger for the negative bubbles than the positive ones. In other words, both in terms of the magnitude of the test statistics and coverage of predictability over the conditional quantiles, monetary policy shocks have a stronger effect on short, medium, and large LPPLS-CIs for the negative bubbles than on the corresponding indicators of positive bubbles. As the negative indicators capture the decline in stock prices before recovery, while positive LPPLS-CIs predict a crash

Table 3 Brock et al. (1996) BDS TEST OF NON-LINEARITY

LPPLS-CI	*m* = 2	*m* = 3	*m* = 4	*m* = 5	*m* = 6
Panel A: target factor					
Positive short-term	18.027***	19.244***	19.978***	20.907***	22.337***
Positive medium-term	15.821***	18.420***	19.770***	21.484***	23.33***
Positive long-term	18.540***	22.557***	26.120***	29.258***	33.105***
Negative short-term	6.604***	5.952***	5.165***	4.589***	4.203***
Negative medium-term	22.736***	24.187***	25.543***	27.223***	29.569***
Negative long-term	9.280***	8.600***	7.306***	6.186***	5.425***
Panel B: path factor					
Positive short-term	18.052***	19.271***	20.005***	20.935***	22.366***
Positive medium-term	15.594***	18.283***	19.660***	21.389***	23.244***
Positive long-term	18.677***	22.575***	26.144***	29.282***	33.099***
Negative short-term	6.029***	5.318***	4.363***	3.639***	2.968***
Negative medium-term	22.876***	24.536***	26.010***	27.933***	30.536***
Negative long-term	8.037***	7.066***	5.772***	4.553***	3.502***

Entries correspond to the *z*-statistic of the BDS test with the null of *i.i.d.* residuals across various dimensions (*m*), with the test applied to the residuals recovered from the multi-scale LPPLS-CI equation with one lag each of the bubble indicators and the target or path factor; *** indicates rejection of the null hypothesis at 1% level of significance

Table 4 Andrews (1993) Breakpoint test

	Positive short-term	Positive medium-term	Positive long-term	Negative short-term	Negative medium-term	Negative long-term
Panel A: target factor						
Max-F	29.375***	21.752***	10.645***	6.732***	13.29***	28.449***
Exp-F	8.030**	5.989***	1.571**	1.269*	13.299***	7.555***
Ave-F	2.236**	6.360***	2.244**	2.210**	0.691	1.775*
Panel B: path factor						
Max-F	29.386***	21.814***	10.067***	6.934***	15.06***	28.561***
Exp-F	8.035**	6.044***	1.442*	1.289*	1.495**	7.612***
Ave-F	2.137**	6.677***	2.159**	2.22**	0.759	1.819*

Entries correspond to the three test statistics of structural breaks, with the test applied to the multi-scale LPPLS-CI equation with one lag each of the bubble indicators and the target or path factor; ***, ** and * indicates rejection of the null hypothesis of structural stability at 1%, 5%, and 10% levels of significance, respectively

after accelerating stock prices, we detect evidence of asymmetry in the effect of monetary policy shocks. The stronger effect on the former may indicate that an expansionary monetary policy is more likely than a contractionary one to revive the Indian stock market in achieving to prick a bubble.[10] This is not surprising as positive bubbles—especially large ones (as tentatively captured by the extreme upper conditional quantiles)—are also likely to be aligned with bubbles in international stock markets (see Fig. 1).

[10] Although robust predictive inference is derived based on the causality-in-quantiles test, it would also be interesting to estimate the sign of the effects of monetary policy shocks on the LPPLS-CIs at various quantiles. However, in a nonparametric framework, this is not straightforward, as we need to employ the first-order partial derivatives. Estimation of the partial derivatives for nonparametric models can experience complications because nonparametric methods exhibit slow convergence rates, which can depend on the dimensionality and smoothness of the underlying conditional expectation function. Hence, the reader is referred to Fig. 3 to derive tentative conclusions in this regard.

Table 5 Causality-in-quantiles test results

Quantile	Positive short-term	Positive medium-term	Positive long-term	Negative short-term	Negative medium-term	Negative long-term
Panel A: target factor						
0.10	1196.319***	957.399***	980.663***	1392.445***	1247.615***	1407.343***
0.20	690.638***	537.128***	565.129***	814.189***	725.048***	827.466***
0.30	444.535***	341.149***	364.840***	535.972***	474.033***	548.765***
0.40	290.461***	222.255***	239.515***	361.255***	316.783***	373.685***
0.50	183.978***	133.881***	152.779***	239.265***	207.318***	251.162***
0.60	107.483***	73.589***	91.021***	150.046***	127.634***	161.114***
0.70	52.942***	37.058***	47.052***	84.160***	69.243***	94.040***
0.80	17.493***	9.200***	17.113***	36.986***	28.806***	45.007***
0.90	0.603	0.206	1.614	7.305***	4.248***	12.285***
Panel B: path factor						
0.10	1147.156***	937.450***	947.211***	1347.417***	1212.734***	1366.928***
0.20	662.229***	526.249***	546.472***	789.101***	705.627***	804.543***
0.30	425.928***	333.471***	352.788***	520.191***	461.721***	533.780***
0.40	278.165***	216.872***	231.440***	351.185***	308.809***	363.520***
0.50	176.077***	130.713***	147.416***	233.085***	202.300***	244.299***
0.60	102.764***	72.381***	87.623***	146.632***	124.725***	156.653***
0.70	50.536***	37.062***	45.106***	82.700***	67.841***	91.368***
0.80	16.681***	9.19***	16.277***	36.800***	28.416***	43.662***
0.90	0.561	0.222	1.507	7.667***	4.347***	11.869***

*** indicates the rejection of the null hypothesis of no Granger causality at the 1% level of significance, i.e., a critical value of 2.575 for the standard normal test statistic, from target or path factor to the multi-scale LPPLS-CIs for a particular quantile

(f) Based on the results in Table 5, we conclude that the predictive impact of the target and path factors varies across the different timescales of the LPPLS-CIs for both positive and negative bubbles. Specifically, for negative bubbles, we observe the strongest impact for the long-term LPPLS-CIs, followed by the short- and medium-term indicators, while for positive bubbles, we observe the strongest effect for the short-term LPPLS-CIs, followed by the long- and medium-term indicators. This finding is relevant as long-term indicators are best suited for detecting larger crashes or rallies, while short-term indicators precede the medium- and long-term LPPLS-CIs. Thus, expansionary monetary policy in India is more likely to be associated with reliable stock market recoveries, whereas the target and path factors may signal the bursting of large bubbles in the future, which are likely associated with extreme movements of global equity markets. Moreover, the asymmetric effect observed in terms of the time scales of the LPPLS-CIs is consistent with the asymmetry in the impact of the target and path factors on positive and negative bubbles. Specifically, the target and path factors have a stronger effect on short-term positive bubbles relative to medium- and long-term indicators. In contrast, the target and path factors have a stronger effect on long-term negative bubbles relative to short- and medium-term indicators. Overall, monetary policy shocks have a stronger effect on short-, medium-, and long-term LPPLS-CIs for negative bubbles compared to positive bubbles.

(g) Finally, regarding the comparison across the predictive content carried by the two monetary policy shocks, we observe that irrespective of the time scales and nature of bubbles (i.e., positive or negative), the target factor[11] is relatively more pronounced than the path factor—a finding in line with those of Lakdawala and Sengupta (2024) on stock returns. In other words, surprise changes to the policy rate target impact bubbles in the Indian stock market more strongly than surprise changes to forward guidance associated with expectations of the stock market about the path for future policy rates. One reason for the lower responsiveness of the bubbles to the path factor could be related to the so-called "information effect" (see, for example, the discussion in Lakdawala and Schaffer (2019) related to stock prices). Monetary announcements convey information that is not only about the current and future stance of monetary policy but also regarding the central bank's internal macroeconomic forecasts. This revelation of information about macro fundamentals comes primarily from the specific language used in the monetary policy statements, which in turn is more likely to be reflected in the path factor than the target factor. In terms of strength of predictability, the roles of the two factors associated with the information contained in monetary policy shocks are evidently different.

In conclusion, we find that the link between stock market bubbles in India and monetary policy shocks is nonlinear and unstable. However, using a nonparametric econometric framework that accounts for these features, we find strong evidence of predictability stemming from monetary policy shocks—particularly the target factor—on the multiscale bubble indicators, especially those associated with negative bubbles. This suggests that Indian monetary policies do have an impact on the stock market bubbles as they do "lean against the wind."

Although a one-to-one comparison with the existing international literature on the effect of monetary policy and stock market bubbles is difficult owing to the obvious differences in terms of methodologies to identify bubbles and then relate the booms and busts to monetary policy shocks, our findings align with the observations derived on this topic for the G7 (Canada, France, Germany, Italy, Japan, United Kingdom [UK], and United States [US]) stock markets. This is because, just as in Caraiani and Călin (2018, 2020) for the US and the Organisation for Economic Co-operation and Development (OECD), and in particular in Caraiani et al. (2023), which also dealt with the MS-LPPLS-CIs but in a panel vector autoregressive (PVAR) model for G7 countries, we observe the predictive effects of monetary policy shocks on the bubble component of stock price. More importantly, however, we indicate that monetary policy can only be used to tackle the formation of bubbles in the equity markets once the RBI realizes the nonlinear and unstable relationship between the two variables of interest, especially when dealing

[11] An alternative to the two-factor approach taken here is to use just the first principal component. Lakdawala and Sengupta (forthcoming) found that the correlation between the first principal component and the target factor is greater than 0.9, while correlation with the path factor is only around 0.3. Thus, in terms of the Indian stock market bubbles response, the first principal component approach would be more akin to just using the target factor, which is vindicated by comparing the results presented in Table 6 in the Appendix of the paper based on the first principal component with those in Table 5 under the target factor.

with high-frequency data, unlike the abovementioned papers, which rely on monthly or quarterly data. To provide a fair comparison, in Table 7 of the Appendix, we present the quantiles-based predictive effect of the target and path factors (derived from Acosta et al. [forthcoming]) on the MS-LPPLS-CIs of the US, starting on the first week of January 1995. The choice of the US was an obvious one owing to publicly available measures of monetary policy shock factors obtained from high-frequency data.[12] In perfect alignment with the findings for India, we find overwhelming causal effects due to monetary policy shocks—especially the target factor—on the multi-scale bubble indicators, particularly for those of the negative bubbles. This suggests the robustness of our results across typical emerging and advanced stock markets.

Conclusion

The primary objective of our study is to analyze the impact of high-frequency monetary policy shocks on equity market bubbles in India, an important emerging country. In this regard, we first detect positive and negative bubbles in the short, medium, and long runs of the Indian stock market by using the Multi-Scale LPPLS Confidence Indicator approach. Our findings revealed major crashes and rallies over the weekly period of November 2003 to December 2020. In the second step, we utilize a nonparametric causality-in-quantiles approach to analyze the predictive impact of monetary policy shocks on the six bubbles indicators. Our results demonstrate strong evidence of predictability for the conditional distributions of the six bubbles indicators based on the nonparametric causality-in-quantiles method, with both the target and path factors of monetary policy shocks showing a relatively stronger impact on the negative bubbles indicators, especially in the long term. This result supports the notion of "leaning against the wind," with expansionary monetary policies being more effective in reviving struggling equity markets under negative bubbles than in controlling positive bubbles, which represent accelerating stock prices resulting from increases in policy rates. Since bubbles affect not only economic activity but also welfare (Narayan et al. 2016), the ability of the Reserve Bank of India (RBI) to manage extreme movements in the equity market—especially at a high frequency—is critical for sustainable economic growth and investor confidence. Our findings also suggest the violation of the efficient market hypothesis in a nonparametric fashion, which indicates that booms and busts in the Indian equity market are driven by fundamental factors such as monetary policy, accounting for nonlinearity, and structural breaks. Therefore, it is crucial for the RBI to recognize the importance of using a nonlinear framework to deal with the relationship between monetary policy and stock market bubbles in India. Academically, our findings also imply the violation of the efficient market hypothesis in a nonparametric fashion, with booms and busts in the Indian equity market being driven by a fundamental—monetary policy—when accounting for misspecification due to nonlinearity and structural breaks.

As part of further research in this area, it would be interesting to extend our study to other emerging stock markets by creating high-frequency monetary policy shocks

[12] The data are available for download from the website of Dr. Miguel Acosta at https://www.acostamiguel.com/research.html, with the reader referred to Caraiani et al. (2023) and van Eyden et al. (2023) for detailed discussion of the behaviour of the bubbles indicators of the US, which has an end-date of the 2nd week of September, 2020.

that span a longer sample period.[13] While we do find strong evidence of predictability from monetary policy shocks on the stock market bubbles in India, the stronger effect at lower conditional quantiles of the bubbles indicators (aligning with the work of Galí (2014), i.e., monetary policy effects depend on the size of the bubbles) may indicate that other factors contribute to the formation of bubbles that we cannot control for in our study owing to the use of a high-frequency approach and a bivariate econometric model. It would be worthwhile to explore other possible high-frequency predictors, such as behavioral factors involving economic sentiment, that may impact bubbles.[14] Although high-frequency indicators of sentiment may not be available at the country-specific level, global sentiment metrics such as the gold price-to-platinum price ratio could be an option.[15] Moreover, in line with the works of Balke and Wohar (2009), Al-Anaswah and Wilfling (2011), and Lammerding et al. (2013), it would be worthwhile to estimate state–space Markov-switching models to detect the regimes of survival and collapse of bubbles and in turn provide an economic explanation for the existence of these two states. Finally, with the tightening of monetary policy being pursued globally to combat the rising inflation rates following the COVID-19 pandemic and the ongoing Russia–Ukraine war, it would be interesting to analyze the associated effect on the crash risk of financial assets, as traditionally captured by realized skewness derived from intraday data (Ben-Nasr et al. 2019).[16]

Appendix A: Quantile-on-quantile (QQ) predictive regression

We study the predictive ability of the monetary policy shocks (x) for the various bubble indicators for India (y, detailed in the data section) using a quantile-on-quantile (QQ) predictive regression model. This method is chosen, as it allows for the change in x, conditional on its current state, to have varied influences on the common factor,

[13] Based on the suggestion of an anonymous referee, even though explicit monetary policy shocks are not available, we conducted a quantiles-based predictive analysis for the MS-LPPLS-CIs of Brazil, China, Russia and South Africa (BCRS) due to the overnight interest rates (provided by Bloomberg), with the reader referred to Gupta et al. (2023) for a detailed discussion of these indicators. Using data for the BCRS respectively, starting on 4th week of October, 2003; 1st week of October, 2006; 2nd week of January, 2010, and; 4th week of March, 2007, and all ending on the 2nd week of September, 2020, our findings were in line with those of India, in the sense that the overnight rate was found to contain a strong predictive content for the entire conditional distributions, particularly at the lower quantiles, of the MS-LPPLS-CIs of these four other emerging countries. Complete details of these results are available upon request from the authors.

[14] Based on the suggestion of any anonymous referee, to control for the behavioural impact on bubbles, we first filtered the MS-LPPLS-CIs by running a linear regression, where the bubbles indicators were regressed on one lag of itself and one lag of the India VIX (IVIX; obtained from: https://www.investing.com), from which the residuals were recovered for the six indicators over the period of 1st week of March, 2008 to 1st week of December, 2020. We then used the nonparametric causality-in-quantiles test to analyse the impact of the two monetary policy shocks factors on these residuals to confirm existence of predictability over the entire conditional distributions of these IVIX-filtered MS-LPPLS-CIs. Complete details of these results are available upon request from the authors.

[15] Considering that gold can be viewed both as a consumption good (mostly jewellery) and an investment tool that preserves value during times of distress, while platinum is a precious metal with similar uses as gold in consumption, Huang and Kilic (2019) argue that gold price-to-platinum price ratio should be largely insulated from shocks to consumption and jewellery demand, and hence provide information on variation in aggregate market risk, serving as a proxy for an important economic state variable.

[16] As a preliminary analysis, we computed monthly realized skewness of the Indian stock market from daily data and related it to the path and target factors, as well as the first principal components, associated with both one- and two-day window changes around the RBI announcement over the period of November, 2003 to February, 2022, based on the recent updates made by Lakdawala and Sengupta (2024). Bivariate linear Granger causality revealed the following p-values of the test running from the path and target factors, and principal component involving the one- and two-day changes to realized skewness as follows: 0.688, 0.622, and 0.330; 0.153, 0.007, and 0.063, respectively. The results suggest strong (weak) linear predictability from the target factor (first principal component) associated with the two-day changes. Complete details of these results are available upon request from the authors.

where a standard quantile regression simply estimates the heterogeneous response of y to x at various points of the conditional distribution of y.

For the ease of estimation, we choose the single equation regression method of Sim and Zhou (2015) for estimating QQ models, over the triangular system of equations-based approach of Ma and Koenker (2006).

Let θ superscript denote the quantile of the y and x under consideration. We first postulate a model for the θ-quantile of y as a function of the x (note this is for the temporaneous relationship). We have:

$$y_t = \beta^{\theta} x_t + \varepsilon_t^{\theta}, \tag{12}$$

where ε_t^{θ} is an error term that has a zero θ -quantile.

As we do not have a prior on how the y and x changes are interlinked, we allow the relationship function $\beta^{\theta}(x_t)$ to be unknown. To examine this linkage between the θ -quantile of y and τ-quantile of x, denoted by x^{τ}, we linearize the function $\beta^{\theta}(x_t)$ by taking a first-order Taylor expansion of β^{θ} (.) around x^{τ}, which yields the following:

$$\beta^{\theta}(x_t) \approx \beta^{\theta}\left(x^{\tau}\right) + \beta^{\theta'}\left(x^{\tau}\right)\left(x_t - x^{\tau}\right) \tag{13}$$

Based on Sim and Zhou's (2015) study, we can redefine $\beta^{\theta}(x^{\tau})$ and $\beta^{\theta'}(x^{\tau})$, respectively, as $\beta_0(\theta, \tau)$ and $\beta_1(\theta, \tau)$. Then, Eq. (9) can be re-written as follows:

$$\beta^{\theta}(x_t) \approx \beta_0(\theta, \tau) + \beta_1(\theta, \tau)\left(x_t - x^{\tau}\right) \tag{14}$$

Ultimately, we substitute Eq. (14) into Eq. (12) to obtain the following:

$$y_t = \beta_0(\theta, \tau) + \beta_1(\theta, \tau)\left(x_t - x^{\tau}\right) + \varepsilon_t^{\theta} \tag{15}$$

Unlike a standard conditional quantile function, the expression

$$\beta_0(\theta, \tau) + \beta_1(\theta, \tau)\left(x_t - x^{\tau}\right) \tag{16}$$

captures the relationship between the θ-quantile of the y and τ-quantile of x, given that β_0 and β_1 are doubly indexed in θ and τ. That is, this expression can capture the overall dependence structure between the y and x through the dependence between their respective distributions.

To estimate (15), we solve for:

$$\min_{01} \sum_{i=1}^{n} \rho_{\theta}[y_t -_0 -_1 (x_t - x \wedge \tau)] K\left(\frac{F_n(x_t) - \tau}{h}\right) \tag{17}$$

to obtain the estimates $\hat{\beta}_0(\theta, \tau)$ and $\hat{\beta}_1(\theta, \tau)$, where the function ρ_{θ} is the tilted absolute value function that provides the θ-conditional quantile of y_t as the solution. Because we are interested in the effect exerted locally by the τ-quantile of x, we employ a Gaussian kernel $K(.)$ to weight the observations in the neighbourhood of x^{τ}, based on bandwidth h (=0.05, following Sim and Zhou (2015)). The weights are inversely related to the distance of x_t from x^{τ}, or more conveniently, the distance of the empirical distribution function

$$F_n(x_t) = \frac{1}{n}\sum_{k=1}^{n} I(x_k < x_t) \tag{18}$$

from τ, where τ is the value of the distribution function that corresponds with x^{τ}.

See Fig. 3, Tables 6, 7.

Table 6 Causality-in-quantiles test results based on the first principal component monetary policy shock

Quantile	Positive short-term	Positive medium-term	Positive long-term	Negative short-term	Negative medium-term	Negative long-term
0.10	1175.239***	952.622***	960.877***	1366.602***	1230.475***	1389.558***
0.20	678.312***	534.709***	553.899***	799.680***	715.456***	817.649***
0.30	436.490***	339.471***	357.376***	526.709***	467.795***	542.425***
0.40	285.231***	220.995***	234.304***	355.180***	312.570***	369.416***
0.50	180.711***	133.128***	149.115***	235.362***	204.49***	248.294***
0.60	105.624***	73.474***	88.500***	147.702***	125.814***	159.257***
0.70	52.069***	37.318***	45.425***	82.946***	68.178***	92.933***
0.80	17.253***	9.439***	16.230***	36.558***	28.304***	44.458***
0.90	0.603	0.213	1.419	7.323***	4.144***	12.127***

*** indicates rejection of the null hypothesis of no Granger causality at the 1% level of significance, i.e., a critical value of 2.575 for the standard normal test statistic, from target or path factor to the multi-scale LPPLS-CIs for a particular quantile

Table 7 Causality-in-quantiles test results for the United States

Quantile	Positive short-term	Positive medium-term	Positive long-term	Negative short-term	Negative medium-term	Negative long-term
Panel A: Target factor						
0.10	1780.099***	1225.587***	1155.970***	2175.286***	1895.977***	2000.058***
0.20	1048.509***	692.513***	667.912***	1272.717***	1110.704***	1175.293***
0.30	670.502***	435.604***	430.966***	838.701***	732.526***	778.461***
0.40	427.645***	277.703***	282.353***	566.971***	494.935***	529.106***
0.50	264.085***	167.982***	179.546***	377.065***	328.915***	354.607***
0.60	149.237***	91.483***	106.785***	238.283***	207.351***	227.010***
0.70	69.108***	41.142***	54.630***	135.440***	117.387***	132.334***
0.80	21.440***	10.997***	19.164***	61.300***	52.682***	63.155***
0.90	0.109	2.337**	3.551**	13.632***	11.381***	16.717***
Panel B: path factor						
0.10	1775.770***	1267.433***	1170.020***	2213.372***	1945.268***	2063.933***
0.20	1045.872***	715.949***	675.723***	1296.995***	1137.811***	1211.459***
0.30	668.593***	450.312***	435.834***	855.159***	749.808***	801.969***
0.40	426.224***	287.281***	285.410***	578.094***	506.354***	544.929***
0.50	263.006***	173.843***	181.365***	384.295***	336.372***	365.174***
0.60	148.433***	94.712***	107.735***	242.605***	211.971***	233.771***
0.70	68.232***	42.607***	54.969***	137.623***	119.935***	136.272***
0.80	20.927***	11.357***	19.115***	62.016***	53.755***	65.021***
0.90	0.078	2.343**	3.459***	13.570***	11.534***	17.186***

*** and **indicate rejection of the null hypothesis of no Granger causality at the 1% and 5% levels of significance respectively, i.e., critical values of 2.575 and 1.96 for the standard normal test statistic, from target or path factor to the multi-scale LPPLS-CIs for a particular quantile

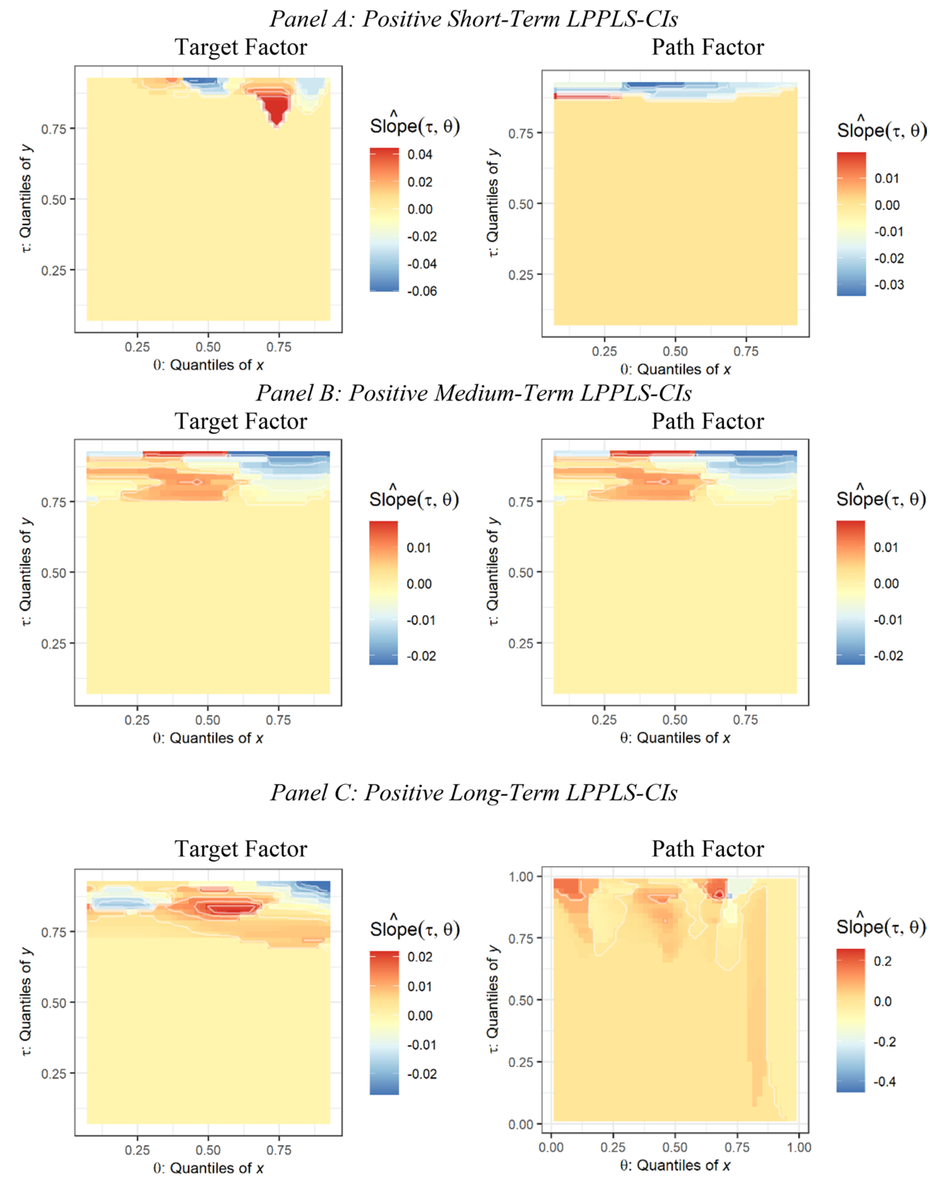

Fig. 3 QQ Plot of the impact of monetary policy shocks on the bubble indicators. *Note y* corresponds to the multi-scale LPPLS-CIs, while *x* is the target or path factor capturing the monetary policy shocks

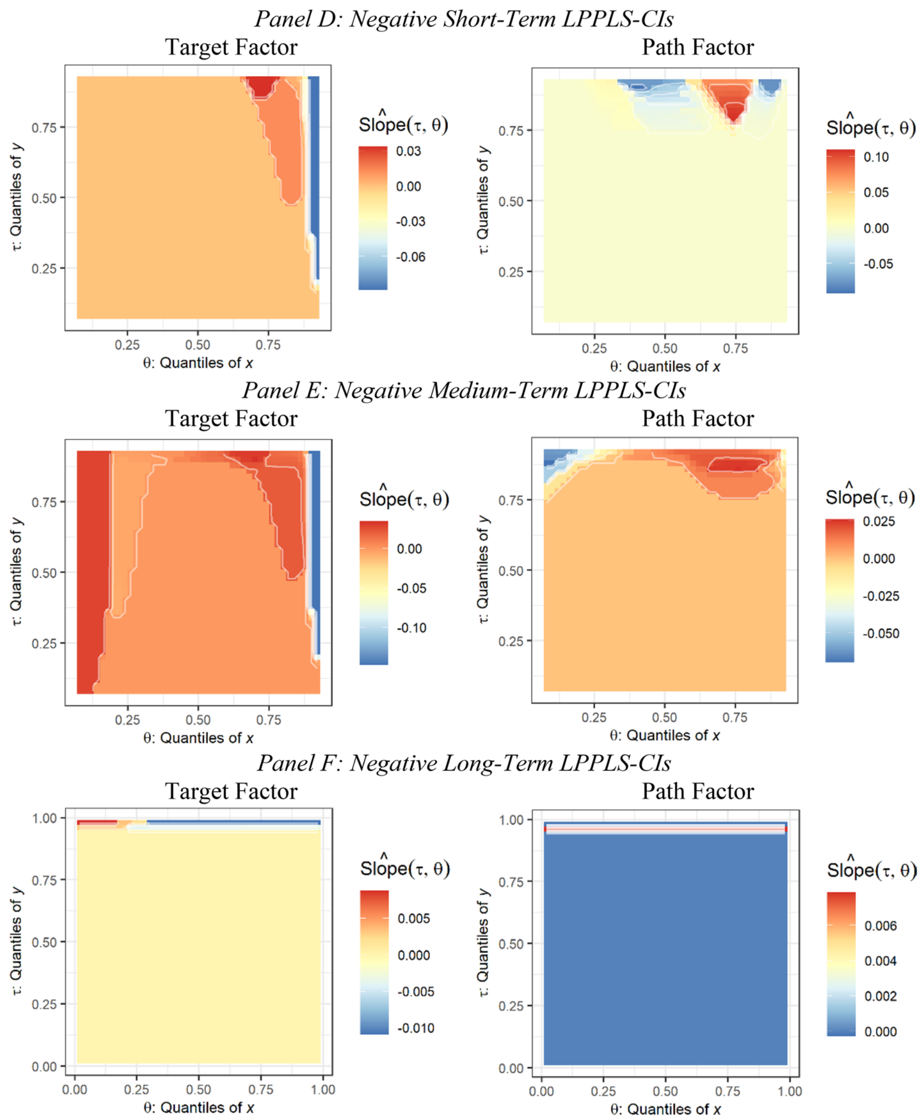

Fig. 3 continued

Abbreviations

BDS	Brock Dechert Scheinkman
BRICS	Brazil, Russia, India, China, and South Africa
GFC	Global financial crisis
HMH	Heterogeneous market hypothesis
i.i.d.	Independent and identically distributed
LPPLS	Log-periodic power law singularity
LPPLS-CI	LPPLS-confidence indicator
MS-LPPLS-CL	Multi-Scale LPPLS-CI
OIS	Overnight index swap
QQ	Quantiles-on-quantiles
RBI	Reserve Bank of India
SLSQP	Sequential least squares programming

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Declarations

Competing interests
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