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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

First, we employ the Multi-Scale Log-Periodic Power Law Singularity Confidence Indicator (MS-LPPLS-CI) approach to identify both positive and negative bubbles in the short-, medium, and long-term for the Indian stock market. We successfully detect major crashes and rallies during the weekly period from November 2003 to December 2020. Second, we utilize a nonparametric causality-in-quantiles approach to analyze the predictive impact of monetary policy shocks on the six bubble indicators. This econometric framework allows us to circumvent potential misspecification due to nonlinearity and instability, rendering the results of no causal influence derived from a linear framework invalid. The two factors of monetary policy shocks namely, the target and path associated with short- and long-term interest rates, reveal strong evidence of predictability for the six bubble indicators across their entire conditional distributions. We observe relatively stronger impacts for the negative bubble indicators due to the target factor rather than the path factor of monetary policy shocks. Our findings have significant implications for the Reserve Bank of India, as well as for academics and investors.

JEL Classification: C22, E52, G10

Keywords: Multi-Scale Positive and Negative Bubbles; Monetary Policy Shocks; Nonparametric Causality-in-Quantiles Test; India

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1. Introduction

According to the discounted cash flow model, stock prices are equal to the present value of expected future net cash flows. As a result, monetary policy shocks can affect stock prices by altering investors' expectations about future cash flows related to economic activity and by 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 (Cepni and Gupta, 2021; Cepni et al., 2021). However, these two channels are interconnected, as more restrictive monetary policy typically implies both higher discount rates and lower future cash flows. Consequently, contractionary monetary policy shocks should correlate with lower stock prices due to higher discount rates for the expected cash flow stream and/or reduced future economic activity. In 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 the case of rational asset price bubbles, the bubble component must grow at the interest rate in equilibrium. Given this, an interest rate increase may end up enlarging the bubble. Furthermore, the theory of rational bubbles suggests that the effects of monetary policy on asset prices should depend on the relative size of the bubble component. In other words, an increase in the interest rate should negatively impact the price of an asset during periods when the bubble component is small compared to the fundamental. This occurs because an interest rate increase always reduces the "fundamental" price of the asset, an effect that should be dominant in "normal" times when the bubble component is small or non-existent. However, if the relative size of the bubble is large, an interest rate hike may end up increasing the asset price over time, due to its positive effect on the bubble outweighing the negative impact on the fundamental component.

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 itself. There is a substantial body of literature on the impact of conventional and unconventional monetary policies (interest rates) on stock market bubbles, 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).[1]

We aim to extend this line of research in the context of an emerging country, specifically 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 well-accepted that the bursting of bubbles can lead to protracted recessions and substantial economic losses (Biswas et al., 2020).[2] Given this, and the fact that India, along with China among emerging markets, is highly integrated with the global financial system (Lakdawala, 2021; Pan and Mishra, 2022), the collapse of the Indian stock market is likely to have negative international spillover effects on both financial and

[1] 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.

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

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 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, India is chosen due to the availability of reliable, relatively long-span, high-frequency publicly available data on monetary policy shocks, as recently developed by Lakdawala and Sengupta (forthcoming). 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 the identification of 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 (Johansen et al., 1999, Johansen et al., 2000, Sornette, 2003) for both positive (upward accelerating price followed by a crash) and negative (downward accelerating price followed by a rally) bubbles. We then apply the multi-scale LPPLS confidence indicators (CI) from Demirer et al. (2019) to characterize positive and negative bubbles at different time scales, specifically short-, medium-, and long-term. These correspond to estimation windows associated with trading activities over one to three months, three months to a year, and one year to two years, respectively. It is worth noting that the identification of both positive and negative multi-scale bubbles is not possible using other available statistical tests (see Balcilar et al. (2016), Zhang et al. (2016), and Sornette et al. (2018) for detailed reviews). We consider this aspect important, as it allows us to gauge the possible asymmetric effect of monetary policy shocks on Indian equity market bubbles. This is because crashes and recoveries at different horizons can convey different information for market participants, as suggested by the Heterogeneous Market Hypothesis (HMH; Müller et al., 1997).[3]

After obtaining the six stock market bubble indicators for India, we analyze the predictive impact of monetary policy shocks on each specific bubble category using the nonparametric causality-in-quantiles test proposed by Jeong et al. (2016). This test enables us to detect predictability across the entire conditional distributions of the LPPLS-CIs, resulting from monetary policy shocks, while simultaneously controlling for misspecification due 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 of the LPPLS-CIs, a quantiles-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), 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 non-existence of predictability due to

[3] 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.

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, since we do not need to determine the number of regimes as in Markov-switching models of causality (Ben Nasr et al. 2015; Balcilar et al. 2018) and can test for predictability at each point of the conditional distribution characterizing specific bubble regimes, our test does not suffer from any misspecification in terms of specifying and testing for the optimal number of regimes.

Although there are some studies examining 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 (forthcoming), 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.

The remainder of the paper is organized as follows: Section 2 outlines the methodologies associated with the detection of bubbles and the nonparametric causality-in-quantiles test. Section 3 is devoted to the discussion of the data. Section 4 presents the empirical results, and Section 5 concludes the paper.

2. Methodologies

2.1. Estimating the Multi-Scale Log-Periodic Power Law Singularity (LPPLS) Model

In this sub-section, we discuss the econometric framework that we utilize to detect our multiscale positive and negative bubbles indicators. Utilizing the LPPLS model, we adopt the stable and robust calibration scheme developed by Filimonov and Sornette (2013):

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

The parameter t_c represents the critical time (the date of the termination of the bubble). A is the expected log value of the observed time-series, i.e., the stock price-dividend ratio, at time t_c. B is the amplitude of the power law acceleration. C is the relative magnitude of the log-periodic oscillations. The exponent of the power law growth is given by m. The frequency of the log-periodic oscillations is given by ω and ϕ represents a phase shift parameter.

Following Filimonov and Sornette (2013), equation (1) is reformulated to reduce the complexity of the calibration process by eliminating the nonlinear parameter ϕ and expanding the linear parameter C to be $C_1 = C \ \cos\phi$ and $C_2 \ = \ C \ \cos\phi$.

The new formulation can be written as

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

where

$$f = (t_c - t)^m$$

$$g = (t_c - t)^m \cos[\omega \ln(t_c - t)]$$

$$h = (t_c - t)^m \sin[\omega \ln(t_c - t)]$$

To estimate the 3 nonlinear parameters: $\{t_c, m, \omega\}$, and 4 linear parameters: $\{A, B, C_1, C_2\}$, we fit equation (2) to the log of the price-dividend ratio. This is done by using L^2 norm to obtain the following sum of squared residuals:

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

Since the estimation of the 3 nonlinear parameters depend on the four linear parameters, we have the following cost function:

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

The 4 linear parameters are estimated by solving the optimization problem:

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

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, the 3 nonlinear parameters can be determined by solving the following nonlinear optimization problem:

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

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 LPPLS confidence indicator, introduced by Sornette et al. (2015), issued to measure the sensitivity of bubble patterns in the log price-dividend ratio time series of each country. The larger the LPPLS confidence indicator (CI), the more reliable the LPPLS bubble pattern and vice versa. It is calculated by calibrating the LPPLS model to shrinking time windows by shifting the initial observation t_1 forward in time towards the final observation t_2 with a step dt. For each LPPLS model fit, the estimated parameters are filtered 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 $B > 0$.

As in the work of Demirer et al. (2019), we incorporate bubbles of varying multiple time-scales into this analysis and sample the time series in steps of 5 trading days. We create the nested windows $[t_1, t_2]$ and iterate through each window in steps of 2 trading days. In this way, we obtain a weekly resolution, based on which we construct the following indicators:

- Short-term bubble: A number $\in [0,1]$ which 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 is comprised of $(90 - 30)/2 = 30$ fits.
- Medium-term bubble: A number $\in [0,1]$ which 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 is comprised of $(300 - 90)/2 = 105$ fits.

- Long-term bubble: A number $\in [0, 1]$ which 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 is comprised of $(745 - 300)/2 = 223$ fits.
- Filter Conditions: After calibrating the model, the following filter conditions 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

$$O = \frac{\omega}{2\pi} \ln\left(\frac{t_c - t_1}{t_c - t_2}\right)$$

$$D = \frac{m|B|}{\omega|C|}$$

2.2. Nonparametric Causality-in-Quantiles Test

In this sub-section, we briefly present the methodology for testing nonparametric quantiles-based causality as developed by Jeong et al. (2012). Let y_t denote a specific LLPLS-CI and x_t the relevant monetary policy shock. Further, let $Y_{t-1} \equiv (y_{t-1}, \dots, y_{t-p})$, $X_{t-1} \equiv (x_{t-1}, \dots, x_{t-p})$, $Z_t = (X_t, Y_t)$, and $F_{y_t|\cdot}(y_t| \bullet)$ denote the conditional distribution of y_t given $\bullet$. Defining $Q_\theta(Z_{t-1}) \equiv Q_\theta(y_t|Z_{t-1})$ and $Q_\theta(Y_{t-1}) \equiv Q_\theta(y_t|Y_{t-1})$, we have $F_{y_t|Z_{t-1}}\{Q_\theta(Z_{t-1})|Z_{t-1}\} = \theta$ 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 has 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 $K(\bullet)$ is the kernel function with bandwidth h, T is the sample size, p is the lag order, and $\hat{\varepsilon}_t = \mathbf{1}\{y_t \le \hat{Q}_\theta(Y_{t-1})\} - \theta$ is the regression error, where $\hat{Q}_\theta(Y_{t-1})$ is an estimate of the θ-th conditional quantile and $\mathbf{1}\{\bullet\}$ is the indicator function. The *Nadarya-Watson* kernel estimator of $\hat{Q}_\theta(Y_{t-1})$ is given by

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

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

The empirical implementation of causality testing via quantiles entails specifying three key parameters: the bandwidth (h), the lag order (p), and the kernel types for $K(\cdot)$ and $L(\cdot)$. We use a lag order of one based on the Schwarz Information Criterion (SIC) and determine h by the leave-one-out least-squares cross validation. Finally, for $K(\cdot)$ and $L(\cdot)$, we use Gaussian kernels.

3. Data

3.1. The Bubble Indicators

The positive and negative weekly bubble indicators at short-, medium-, and long-term for India are derived based on the natural logarithmic values of the daily price-to-dividend ratio. The dividend and stock price index series, in their local currencies, are individually obtained from Refinitiv Datastream. It is important to note that, since we use the price-dividend ratio in line with the existing literature, the underlying metric for obtaining the bubble indicators is free of any currency units and is 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 sub-section 2.1, is sampled at a weekly frequency, as shown below and depicted in Figure 1.

[INSERT FIGURE 1]

The short-, medium-, and long-term indicators are displayed in different colors (green, purple, and red, respectively), while the log price-to-dividend ratio is shown in black in Figure 1. Higher LPPLS-CI values for a particular 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. There are notably fewer long-term negative LPPLS-CI values, 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 due 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 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, while the 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 could potentially be influenced differently by Indian monetary policy shocks, as represented by the target and path factors.

3.2. Monetary Policy Shocks

With regard to the metrics of monetary policy shocks, we rely on the recent work by Lakdawala and Sengupta (forthcoming) in this contex.[4] 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 (forthcoming) 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.[5] Furthermore, by utilizing OIS rates of various maturities (1-, 3-, 6-, 9-month, and 1-year), Lakdawala and Sengupta (forthcoming) capture any potential information obtained by the market regarding the future path of the policy rate from RBI communication.

Technically speaking, Lakdawala and Sengupta (forthcoming) 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, since these principal components are correlated with both the short- and long-end of the OIS rate curve, they cannot be assigned any economic meaning. To provide a structural interpretation, the authors transformed these two principal components into the so-called "target" and "path" factors, following Gürkaynak et al. (2005). The target factor captures surprise changes to the reserve bank's short-term policy rate target, while the path factor contains information on surprise changes to forward guidance or any surprise news that leads markets to change their expected path for future policy rates. Just like the principal components, these two factors are constructed to be orthogonal to one another, ensuring 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 (forthcoming). The path and target factors are depicted in Figure 2.

[INSERT FIGURE 2]

Lakdawala and Sengupta (forthcoming) used a narrative analysis to confirm the reliability of the OIS rates, and thus 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 significant changes in the factors, Lakdawala and Sengupta (forthcoming) concluded that the factors capture surprises that align with their interpretation of the RBI decisions, the language used in the statements, and the corresponding media discussion.

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

[5] 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).

Based on availability of data of the monetary policy shocks, our analysis covers the weekly period of 3rd (1st week of) November, 2003 to 4th (1st week of) December, 2020, i.e., 882 observations. It is important to note that the path and target factors have values of zero on non-announcement days. The data is summarized in Table 1, and as can be observed, the bubble indicators (as well as the monetary policy shocks) are non-normal. This provides an initial motivation for our quantiles-based causality framework.

[INSERT TABLE 1]

To gain an initial understanding of the correlation between bubble indicators and monetary policy shocks, we refer to Figure A1, which displays the conditional quantiles-based response of the former, stemming from various quantiles of the latter. 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, 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 bubble indicators are likely to decrease (increase) in value, as they capture rapidly declining stock prices before recovery and accelerating prices before a crash.

4. 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 can draw the following observations from the predictive analyses:

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, there is 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.

(a) Having observed no evidence of causality based on the linear specification, we next examine whether the finding of non-causality might be due to model misspecification that assumes a linear predictability relationship. Therefore, in order to explore whether the linear model is misspecified, we first test for the presence of nonlinearity in the relationship between the six LPPLS-CIs and the two monetary policy shocks. In this regard, we use the Brock et al. (1996, BDS) test on the residuals from the linear model used in the linear Granger causality tests, and check whether the null hypothesis of *i.i.d.* residuals at various dimensions (m) can be rejected or not. Table 3 presents the results of the BDS nonlinearity tests. As shown in the table, the BDS test yields overwhelming evidence of nonlinearity, that is, we reject the null hypothesis of linearity (*i.i.d.* residuals) at the highest level of significance, consistently across all 12 predictive cases considered. In sum, the BDS test confirms that the linear model is indeed misspecified due to the existence of uncaptured nonlinearity, and hence, further predictive inference must rely on a nonlinear model, which happens to be our nonparametric causality-in-quantiles approach.

(b) 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 due 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 that there is widespread evidence of regime changes, with the strongest results of parameter instability derived under the *Max-F* test. Given that 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.

(c) 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 us with a 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 to 0.90, we can draw the following important conclusions:

(i) 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 on 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 the corresponding indicators of positive bubbles. Since the negative indicators capture decline in stock prices before recovery, while positive LPPLS-CIs predict a crash after accelerating stock prices, we detect evidence of asymmetry in the effect of monetary policy shocks. The stronger effect on the former is perhaps an indication that expansionary monetary policy is more likely to revive the Indian stock market than a contractionary one in achieving to prick a bubble.[6] 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 – an observation that is vindicated by Figure 1;

(ii) Based on the results in Table 5, we can conclude that the predictive impact of the target and path factors varies across the different time-scales of the LPPLS-CIs for both positive and negative bubbles. Specifically, for negative bubbles, the strongest impact is observed for the long-term LPPLS-CIs, followed by the short- and medium-term indicators, while for positive bubbles, the strongest effect is observed for the short-term LPPLS-CIs, followed by the long- and medium-term indicators. This finding is significant because 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, the results suggest that 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 burst 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 observed 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, these findings indicate that monetary policy shocks have a stronger effect on short-, medium-, and long-term LPPLS-CIs for negative bubbles compared to positive bubbles.

(iii) Finally, with regard to 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[7] is relatively more pronounced than the path factor – a

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[6] 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 Figure A1 to derive tentative conclusions in this regard.

[7] 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 A1 in the Appendix of the paper based on the first principal component with those in Table 5 under the target factor.

finding in line with those made by Lakdawala and Sengupta (forthcoming) on stock returns. In other words, surprise changes to the policy rate target impacts 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). The idea is that 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 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 role of the two factors associated with the information contained in monetary policy shocks are evidently different.

[INSERT TABLES 2, 3, 4, AND 5]

In conclusion, we discover that the link between stock market bubbles in India and monetary policy shocks is non-linear and unstable. However, by using a non-parametric econometric framework that accounts for these features, we find strong evidence of predictability stemming from the monetary policy shocks, particularly the target factor, on the multi-scale 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".

4. Conclusion

The primary objective of our paper is to analyze the impact of high-frequency monetary policy shocks on equity market bubbles of an important emerging country namely, India. In this regard, we first detect positive and negative bubbles at short-, medium- and long-run for 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 analyse 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 at the long-term time scale. 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 not only impact the 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 is critical for sustainable economic growth and investor confidence. Our findings also suggest the violation of the efficient market hypothesis in a nonparametric fashion, indicating 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.

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 that span a longer sample period. 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 may indicate that other factors contribute to the formation of bubbles that we cannot control for in our study due 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 behavioural factors involving economic sentiment, that may impact bubbles. Although high-frequency indicators of sentiment may not be available at the country-specific level, global sentiment metrics like the gold price-to-platinum price ratio could be an option.[8]

[8] 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.

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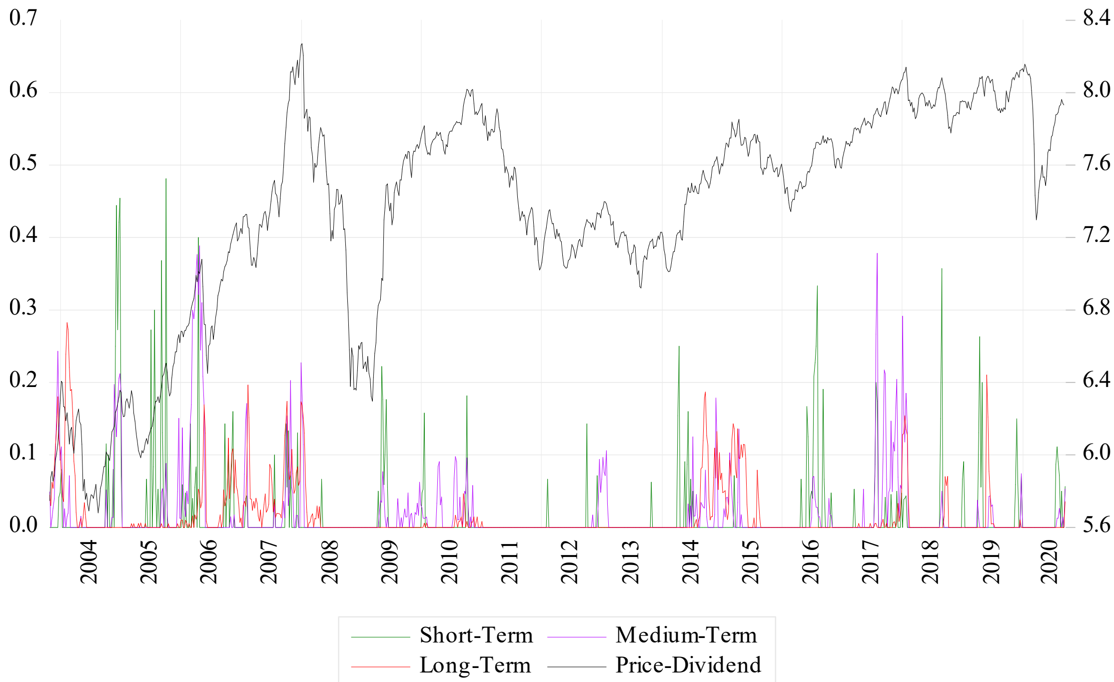
Figure 1: Bubble Indicators and Log of Price-Dividend Ratio

Panel A: Positive Bubble Indicators



Panel B: Negative Bubble Indicators

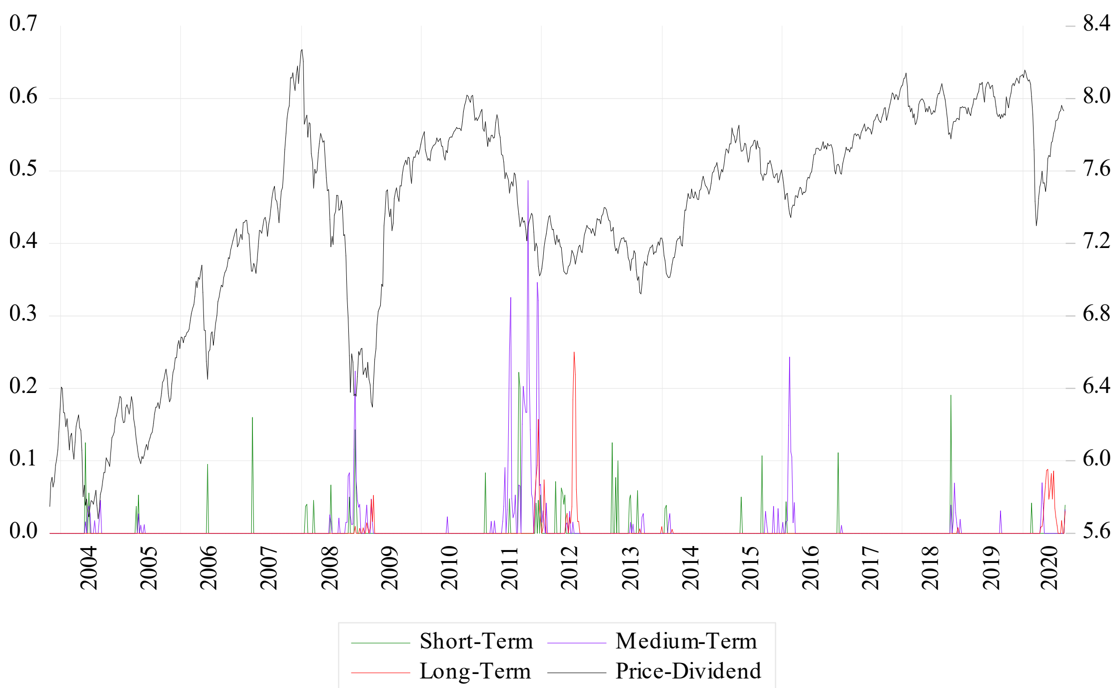
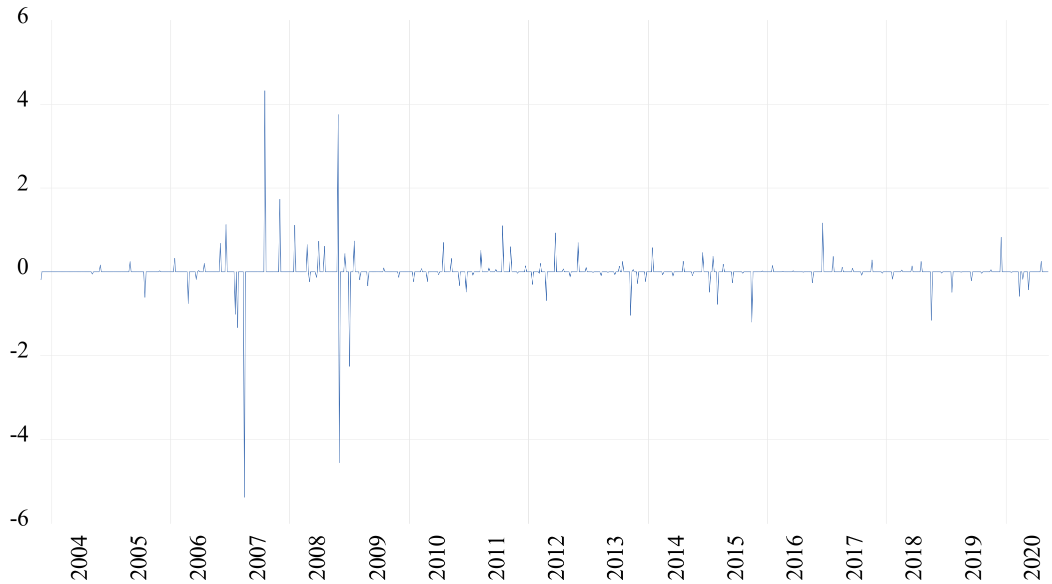


Figure 2: Monetary Policy Shocks

Panel A: Target Factor



Panel B: Path Factor

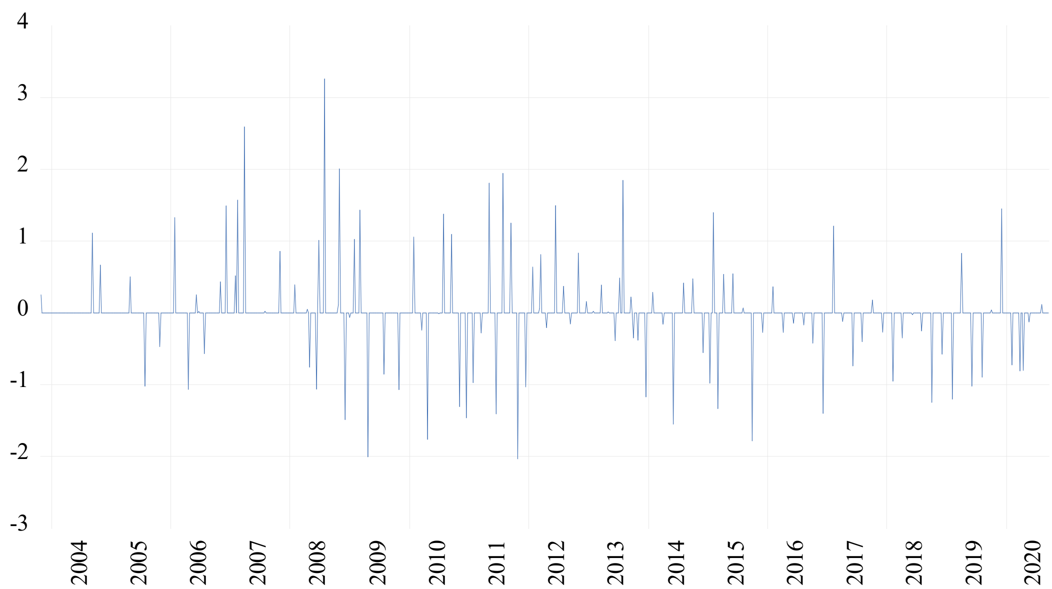


Table 1: Summary Statistics

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	33204***	13925***	6622***	138887***	191651***	463081***	568152***	17812***
Observations	882	882	882	882	882	882	882	882

Note: 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.

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

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

Table 3: Brock et al. (1996) BDS Test of Non-Linearity

Panel A: Target Factor

LPPLS-CI	m=2	m=3	m=4	m=5	m=6
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

LPPLS-CI	m=2	m=3	m=4	m=5	m=6
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***

Note: 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

Panel A: Target Factor

	Positive Short-Term	Positive Medium-Term	Positive Long-Term	Negative Short-Term	Negative Medium-Term	Negative Long-Term
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

	Positive Short-Term	Positive Medium-Term	Positive Long-Term	Negative Short-Term	Negative Medium-Term	Negative Long-Term
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*

Note: 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.

Table 5: Causality-in-Quantiles Test Results

Panel A: Target Factor

Quantile	Positive Short-Term	Positive Medium-Term	Positive Long-Term	Negative Short-Term	Negative Medium-Term	Negative Long-Term
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

Quantile	Positive Short-Term	Positive Medium-Term	Positive Long-Term	Negative Short-Term	Negative Medium-Term	Negative Long-Term
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***

Note: *** indicate rejection of the null hypothesis of no Granger causality at the 1% level of significance, i.e., 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.

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 the for the change in x, conditional on its current state, to have varied influences on the common factor, 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:

$$y_t = \beta^{\theta} x_t + \varepsilon_t^{\theta} \ , \tag{A1}$$

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:

$$\beta^{\theta}(x_t) \approx \beta^{\theta}(x^{\tau}) + \beta^{\theta\prime}(x^{\tau})(x_t - x^{\tau}) \tag{A2}$$

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

$$\beta^{\theta}(x_t) \approx \beta_0(\theta,\tau) + \beta_1(\theta,\tau)(x_t - x^{\tau}) \tag{A3}$$

Ultimately, we substitute equation (A3) into equation (A1) to obtain the following:

$$y_t = \beta_0(\theta,\tau) + \beta_1(\theta,\tau)(x_t - x^{\tau}) + \varepsilon_t^{\theta} \tag{A4}$$

Unlike a standard conditional quantile function, the expression

$$\beta_0(\theta,\tau) + \beta_1(\theta,\tau)(x_t - x^{\tau}) \tag{A5}$$

captures the relationship between the θ-quantile of the y and τ-quantile of x, given that $\beta_0$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 (A4), we solve for:

$$\min_{\beta_0 \beta_1} \sum_{i=1}^{n} \rho_{\theta} \left[y_t - \beta_0 - \beta_1(x_t - x\hat{}\tau)\right] K\left(\frac{F_n(x_t) - \tau}{h}\right) \tag{A6}$$

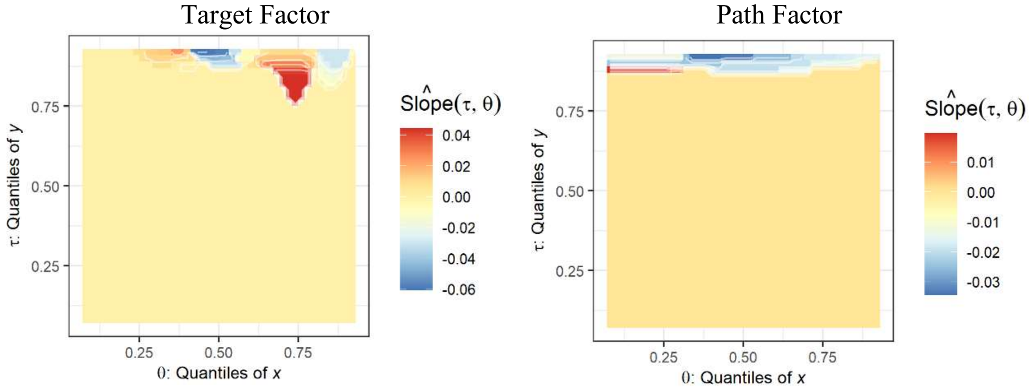
to obtain the estimates $\hat{\beta}_0(\theta,\tau)$ and $\hat{\beta}_1(\theta,\tau)$, where the function ρ_θ is the tilted absolute value function that provides the θ-conditional quantile of y_t as the solution. Because we are interested in the effect exerted locally by the τ-quantile of x, we employ 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

$$F_n(x_t) = \frac{1}{n}\sum_{k=1}^{n} I(x_k < x_t) \tag{A7}$$

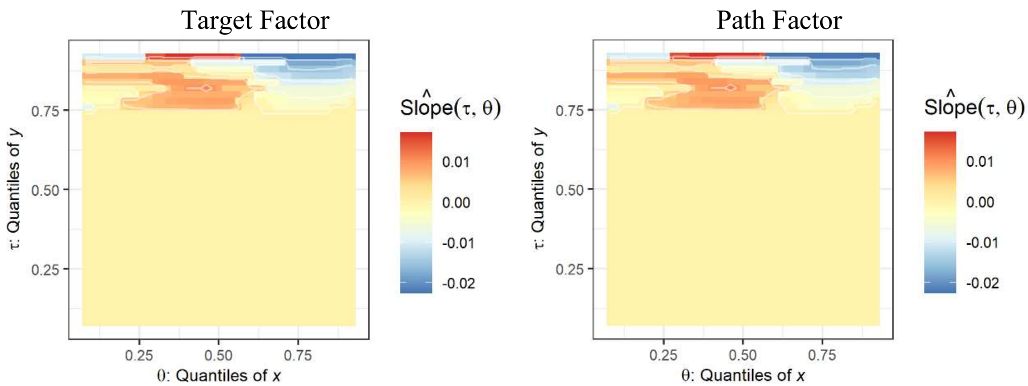
from τ, where τ is the value of the distribution function that corresponds with x^τ.

Figure A1: QQ Plot of the Impact of Monetary Policy Shocks on the Bubble Indicators

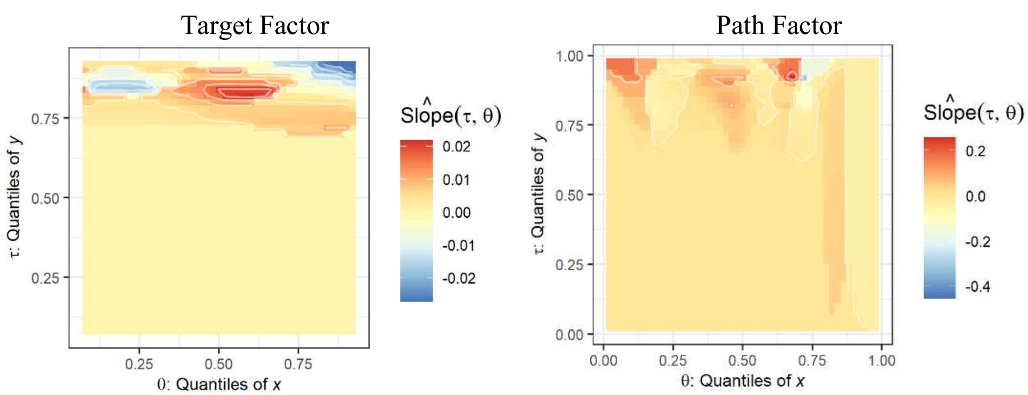
Panel A: Positive Short-Term LPPLS-CIs



Panel B: Positive Medium-Term LPPLS-CIs

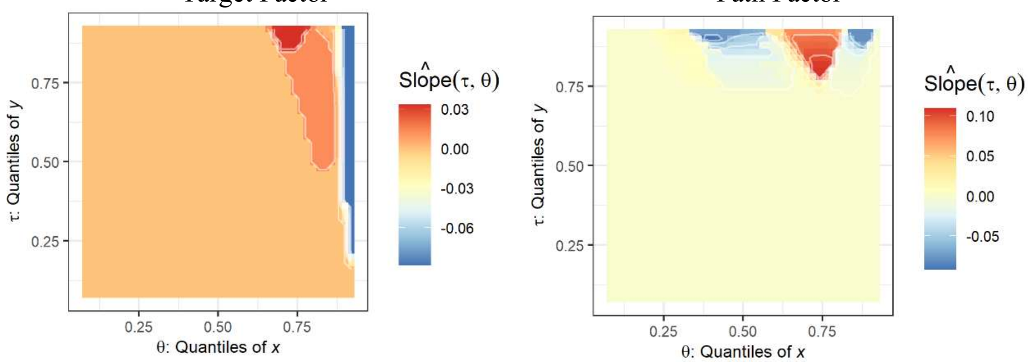


Panel C: Positive Long-Term LPPLS-CIs



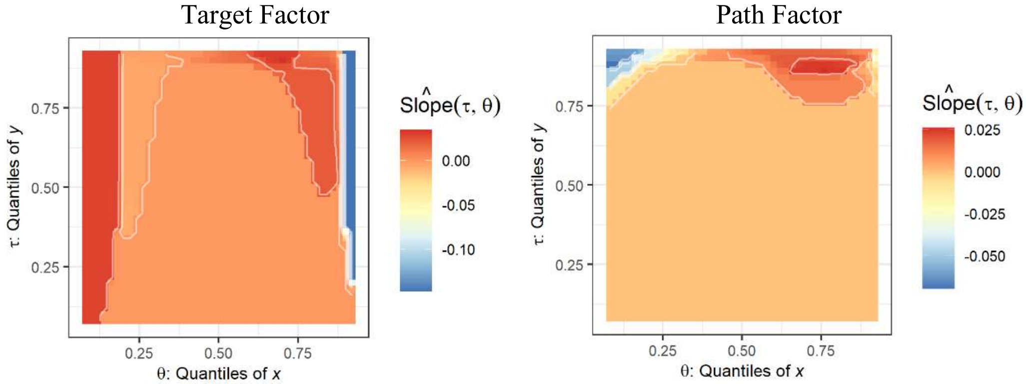
Panel D: Negative Short-Term LPPLS-CIs

Target Factor Path Factor



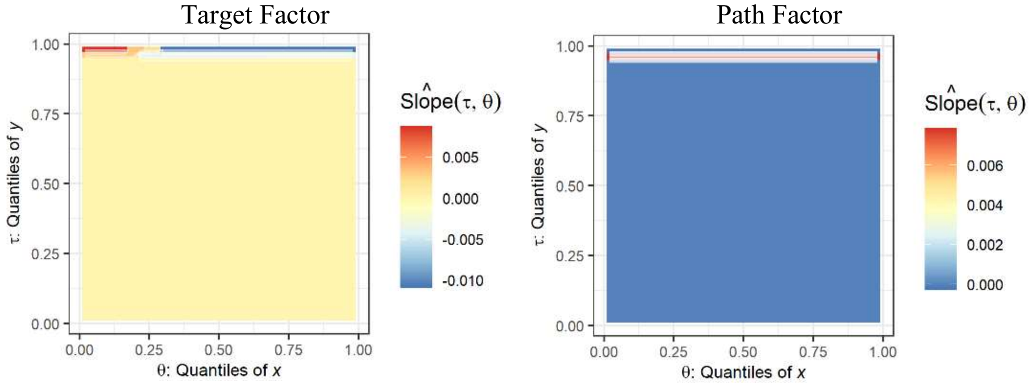
Panel E: Negative Medium-Term LPPLS-CIs

Target Factor Path Factor



Panel F: Negative Long-Term LPPLS-CIs

Target Factor Path Factor



Note: *y* corresponds to the Multi-Scale LPPLS-CIs, while *x* is the Target or Path Factor capturing the monetary policy shocks.

Table A1: 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***

Note: *** indicate rejection of the null hypothesis of no Granger causality at the 1% level of significance, i.e., 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.