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Reference: Gupta, Rangan/Nel, Jacobus et. al. (2022). US monetary policy and BRICS stock market bubbles. Pretoria, South Africa : Department of Economics, University of Pretoria.
https://www.up.ac.za/media/shared/61/WP/wp_2022_43.zp224083.pdf.

This Version is available at:
http://hdl.handle.net/11159/12299

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Rangan Gupta
University of Pretoria
Jacoubs Nel
University of Pretoria
Joshua Nielsen
Boulder Investment Technologies

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Department of Economics
University of Pretoria
0002, Pretoria
South Africa
Tel: +27 12 420 2413

US Monetary Policy and BRICS Stock Market Bubbles

Rangan Gupta[*], Jacobus Nel[†], Joshua Nielsen[‡]

Abstract

We use the multi-scale Log-Periodic Power Law Singularity (LPPLS) confidence indicator approach to detect both positive and negative bubbles at short-, medium- and long-run for the stock markets of the BRICS countries. We were able to detect major crashes and rallies in the five stock markets over 2nd week of February, 1999 to 2nd week of September, 2020. We also observed similar timing of strong (positive and negative) LPPLS indicator values across the countries, suggesting interconnectedness of the extreme movements in these stock markets. Then, we utilize impulse responses obtained from the local projection method (LPM) framework to capture the effect of US monetary policy shocks on a specific-type of bubble of a particular equity market of the BRICS bloc, by controlling for lagged values of the category of bubble under consideration of all the five countries, due to the synchronicity of bubbles. In general, the effect of US monetary policy shocks on the six bubble indicators for each country is limited, with strong positive impact observed under the medium-term negative bubble indicator of Brazil, China and South Africa. Given the findings, associated policy implications are discussed.

JEL Classification: C22, E52, G15

Keywords: Multi-Scale Bubbles, Local Projection Method, US Monetary Policy, BRICS Countries

[*]Department of Economics, University of Pretoria, Private Bag X20, Hatfield 0028, South Africa; Email address: rangan.gupta@up.ac.za

[†]Department of Economics, University of Pretoria, Private Bag X20, Hatfield 0028, South Africa; Email address: neljaco380@gmail.com

[‡]Boulder Investment Technologies, LLC, 1942 Broadway Suite 314C, Boulder, CO ,80302, USA; Email address: josh@boulderinvestment.tech.

1. Introduction

The increased integration of stock markets of emerging countries with that of the developed world over the last few decades is now a well-established fact (Mobarek and Mollah, 2016). In the process, equity markets in emerging economies are likely to be driven by monetary policies of advanced countries, especially that of the United States (US), which is known to be a major driver of the global financial cycle (Miranda-Agrippino and Rey, 2020). Theoretically, the transmission of monetary policy shocks of the US to foreign stock markets can be explained via the dividend discount model, which posits that the value of a stock is the sum of all future dividends discounted by expected stock returns. Given this, monetary policy surprises of the US can impact emerging market stock prices by either changing expected stock returns, i.e. the risk perception of investors, or expectation about future dividends, which is associated with the outlook for the real economy. In general, there exists persuasive empirical evidence that expansionary US monetary policy shocks tend to be associated with rising stock prices worldwide, including emerging countries (see, Lakdawala (2021), and Maurer and Nitschka (2021) for detailed reviews of this literature).

We aim to build on this line of research, but instead of stock prices per se, we concentrate on the impact of US monetary policy shocks on the extreme behavior, i.e., bubbles, of the stock markets of five major emerging economies namely, Brazil, Russia, India, China and South Africa (BRICS) countries.[1] In this regard, we cover the weekly period of 2nd week of February, 1999 to 2nd week of September, 2020, and use a common metric of monetary shocks, as developed by Bua et al. (2021), which captures both conventional and unconventional monetary policy decisions of the US Federal Reserve characterizing our data sample. As far as detecting bubbles are concerned, we not only use the Log-Periodic Power Law Singularity (LPPLS) model (Johansen et al., 1999, 2000; Sornette, 2003), for both positive (upward accelerating price followed by a crash) and negative (downward accelerating price followed by a rally) bubbles, but we then apply the multi-scale LPPLS confidence indicators (CI) of Demirer et al. (2019) to characterise positive and negative bubbles at different time scales, i.e., short-, medium- and long-term. Note that, identification of both positive and negative multi-scale bubbles is not possible based on other available wider array of statistical tests (see, Balcilar et al. (2016), Zhang et al. (2016), and Sornette et

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[1]These five countries are already contributing to more than a quarter of global output, with the bloc expected to constitute more than 45% of the world's stock market capitalization by 2030 (Bouoiyour and Selmi, 2016; Bouri, et al., 2020). Naturally, the BRICS stock markets carries immense potential for international portfolio diversification.

al. (2018) for detailed reviews). We consider this as important, since this would allow us to gauge the possible asymmetric effect of US monetary policy shocks on the equity market bubbles of the BRICS, given that crash and recovery at different horizons can carry different information for market participants, as suggested by the Heterogeneous Market Hypothesis (HMH; Müller et al., 1997).[2] Once we obtain the six bubble indicators for each of the five countries, we analyze the impact of the US monetary policy shock on the specific bubble category of a particular country, by controlling for lagged bubble indicators of the corresponding category belonging to all the members of the BRICS bloc (to capture the high degree of synchronization of bubbles, which we discuss in detail below). Specifically speaking from the perspective of an econometric model, the US monetary policy shock is used to obtain impulse response functions (IRFs) for the bubble indicators by feeding the monetary surprises into the local projection method (LPM) of Jordà (2005).

To the best of our knowledge, this is the first paper to analyze the effect of conventional and unconventional US monetary policy surprises on the multi-scale positive and negative bubbles of the BRICS based on IRFs obtained from a LPM. At this stage, it is important to emphasize that extreme movements in stock markets have major implications for the real economy (Caraiani et al., forthcoming), and understanding the role of US monetary policy in this regard carries valuable information for the domestic policymakers of these emerging economies in terms of designing their own policy response to the boom-bust cycle of stock markets (Rajan, 2015). The remainder of the paper is organized as follows: Section 2 discusses the data, while Section 3 outlines the basics of the LPM. Section 4 discusses the empirical findings involving detection of the bubbles, as well as the effects of US monetary policy shocks on the detected bubbles of the BRICS. Finally, Section 4 concludes the paper.

2. Data

The positive and negative weekly bubble indicators at short-, medium-, long-term for each of the BRICS countries are derived based on the natural logarithmic values of the daily dividend-price ratio, with the dividend and the stock price index series, in their local currencies, obtained from Refinitiv Datastream. The Appendix of the paper outlines the mathematical details of how the multi-scale LPPLS CIs are

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[2]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.

obtained. Each of the derived multi-scale LPPLS-CI values for the BRICS countries sampled at a weekly frequency are discussed in the following section of the paper, and depicted in Figure 1.

As far as the metric of the US monetary policy shock (MP) is concerned, we use the shocks derived by Bua et al. (2021), who utilize a two-step regression approach to estimate the unobservable monetary policy shock.[3] In the first step, the authors run time-series regressions to estimate the sensitivity of zero-coupon yields at maturities of 1 year to 30 years to Federal Open Market Committee (FOMC) announcements. At this step, Bua et al. (2021) also employ a instrumental variables heteroskedasticity-based estimator to filter out non-monetary policy news. In the second step, for each time, the authors regress all outcome variables onto the corresponding estimated sensitivity index from step one. In this way, the monetary policy shock, as also included in Figure 1, is derived as the series of estimated coefficients from the second-step regression.[4]

Given data availability, our paper covers the sample period of 2nd week of February, 1999 to 2nd week of September, 2020. In this regard, note that, usage of weekly, rather than daily, data allows us to include the information of the equity market bubble indicators in our econometric model simultaneously and match with (173) FOMC meetings date-based US monetary policy shocks,[5] as we no longer need to be concerned about the time-differences in the respective opening and closing times of both the stock and gold markets.

3. Methodology

To examine the impact of the US monetary policy shock on the six bubble indicators for each country, we employ the LPM approach of Jordà (2005). The model

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[3]The data is freely available for download from the research segment of the website of Professor Wenbin (Ben) Wu: https://sites.google.com/view/wenbinwu-ucsd/research?authuser=0.

[4]In the process, the derived monetary policy shock series has three appealing features. First, the measure bridges periods of conventional and unconventional monetary policy decisions in a stable fashion. Second, the estimation approach has very mild data requirements, as there is no need to parse through Federal Reserve transcripts and forecasts, or use intraday data. Third, the generated series is shown to be largely unpredictable from available information on the economy, and also does not contain any significant central bank information effect. Hence, it ensures cleaner inference on the transmission of exogenous shocks of US conventional and unconventional monetary policy to bubbles of the BRICS countries.

[5]Understandably, for the weeks when there is no FOMC meeting, the value of the shock is taken to be zero.

for computing LPM-based IRFs is as follows:

$$y_{t+s}^n = \alpha_s + \beta_s MP_t^{US} + \gamma_s(L)X_{t-1} + \epsilon_{t+s} \tag{1}$$

where y is the specific bubble indicator of a particular country, s is forecast horizon, with $s = 0,1,2,\ldots, h$, whereby h is the maximum length of the forecast horizons, which we set to 8. MP_t^{US} represents the US monetary policy shock at time t, X is a vector of control variables, $\gamma_s(L)$ is a polynomial in the lag operator, with a lag-length of 1 chosen by the Schwarz Information Criterion (SIC). Our vector of control variables in X basically contains the lags of the specific type of bubbles of the BRICS that are being analyzed, in light of the high degree of synchronization across the five countries for a specific bubble type, as is discussed in detail below.

The coefficient β_s measures the response of the y_t^n at time $t + s$ to an one unit change in the monetary policy shock at time t. The IRFs can be constructed as a sequence of β_s estimated in a series of single regressions for each horizon(s). It must be pointed out that, the impulse responses can be computed without specification and estimation of the underlying multivariate dynamic system. The central idea consists in estimating local projections at each period of interest rather than extrapolating into increasingly distant horizons from a given model, as it is done within the context of a vector autoregressive (VAR) model. In other words, the analysis of the impact on y_t^n to the US monetary policy shock (MP_t) does not require identification based on a certain scheme, say for example, the Cholesky decomposition.

4. Empirical Findings

4.1. Detection of Bubbles

The short-, medium- and long-term indicators are displayed in different colors (green, purple and red, respectively), and the log price-to-dividend ratio is displayed in black in Figure 1. Higher LPPLS-CI values from a corresponding scale indicate that the LPPLS signature is present for many of the fitting windows to which the model was calibrated, and hence is more reliable.

[INSERT FIGURE 1 HERE]

We observe two strong long-term positive LPPLS-CI regimes. The first precedes the GFC, especially for Brazil, China and India. The second emerges between 2014 and 2018. There are notably fewer long-term negative LPPLS-CI values, with the most apparent negative bubble for this scale occuring after the GFC, capturing recovery. We see pronounced LPPLS-CI values for both positive and negative bubbles

everywhere we observed the spikes in the long-term indicators. In addition, we see strong positive medium-term LPPLS-CI values emerge prior to strong long-term LPPLS-CI values leading up to the GFC. For all BRICS countries except Russia, we see a small rally signaled by a negative short-term LPPLS-CI value in late 2002, likely associated with the recovery following the technological stocks sell-off.

In general, long-term scales produces fewer signals, but appear to pick-up larger crashes or rallies, while the smaller scales produces more signals that precede smaller crashes or rallies. We also observed similar timing of strong (positive and negative) LPPLS-CI values across the BRICS countries, lending to the idea that extreme movements in the stock markets of these major emerging market economies tend to be aligned.[6] Overall, the empirical findings support the claims that the LPPLS framework is a flexible tool for detecting bubbles across different time-scales. In addition, both positive and negative bubbles indicators at the three scales, seem to carry unique information, and could possibly be impacted differently by the US monetary policy shock.

4.2. US Monetary Policy and Bubbles of the BRICS Stock Markets

In Figures 2(a), 2(c) and 2(e), we present the impact of one unit increase in the US monetary shock on short, -medium-, and long-term positive bubbles respectively, while Figures 2(b), 2(d) and 2(f) does the same for the negative bubbles, along with the 95% confidence bands. Before we discuss the results, recall that, a positive bubble indicator signals rapid growth in the stock markets before the crash, while the negative bubble indicator captures the recovery following a decline. In other words, intuitively, a contractionary monetary shock in the US, which is known to negatively impact foreign stock prices via the dividend discount model, should have a negative effect on the positive bubble indicators, and a positive effect on the negative bubble indicators.

Keeping this in mind, we find that, intuitively-consistent mildly significant short-

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[6]In this regard, we computed Total Connectedness Indexes (TCIs) using the Time-Varying Parameter Vector Autoregressive (TVP-VAR) approach of Antonakakis et al. (2020), to which the reader is refereed to for the technical details. This connectedness measure indicates the degree of network interconnectedness of the bubble indicators, and provides us with six TCIs for the BRICS, which basically corresponds to the six different bubbles indicators of the countries that were included in six separate TVP-VARs to obtain the TCIs for BRICS bloc. The TCIs have been plotted in Figure A1 in the Appendix, and highlights strong connectedness especially at the medium- and long-term for both positive and negative bubbles. Furthermore, the TCIs are, in general, found to rise during the identified periods of bubbles, corresponding to higher values of the LPPLS-CI observed in Figure 1.

lived negative effects are observed for South Africa and China only under the cases of positive short- and long-term bubbles respectively. As far as the negative bubbles are concerned, intuitively-aligned significant positive impacts are observed for China in the case of the short-term indicator; Brazil, China and South Africa (with a delay) under the medium-term indicator, and; very mildly significant for India, when we look at the long-term indicator. So, compared to the positive bubbles, especially when we look at the medium-term, US monetary policy tends to impact negative bubbles more strongly in terms of the strength and persistence of the significant effects, as well as the number of countries. Russia is the only country within the bloc, which has no significant impact on any of its bubble indicators due to US monetary policy decisions,[7] with China and South Africa showing the most degree of impact.

Given that the recent literature has primarily concentrated on the effect of un-conventional monetary policy on stock markets of emerging countries, we carried out a sub-sample analysis over 2nd week of February, 1999 to 4th week of December, 2006, and 1st week of January, 2007 to 2nd week of September, 2020. As can be seen, from Figures A2 and A3 in the Appendix of the paper, the full-sample results reported in Figure 2, is basically driven by the second sub-sample,[8] and aligns with the findings in this line of research that emerging financial markets have been more responsive to unconventional, rather than conventional, monetary policy actions of the US (see for example, Ono (2020)).

Overall, US monetary policy shocks seem to primarily drive medium-term nega-tive bubbles of Brazil, China and South Africa. Given this, a contractionary mone-tary policy pursued in the US will delay the revival of the stock market of these three countries in the medium-run. Recall that the longer time-scales are best-suited for detecting larger crashes or rallies, but also short- and medium-term indicators pre-cede the long-term indicators. In light of this, the fact that monetary shock tends to impact the medium-run bubble indicators in these countries, in the strongest man-ner, expansionary policy decisions of the US can lead a recovery in Brazil, China and South Africa in a timely manner. In the same vein, some weak evidence of the influence of US monetary policy is also detected for positive bubbles in China and South Africa, whereby there is a small chance of a crash due to a contractionary monetary policy in the US.

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[7]This could possibly be due to the overwhelming importance of oil in driving the Russian equity market (Cakan et al., 2019).

[8]An exception is the positive and significant effect on the medium-term negative bubble indicator for India under the first sample period.

[INSERT FIGURE 2 HERE]

5. Conclusion

The primary objective of our paper is to analyze the impact of conventional and unconventional monetary policy shocks of the US on equity market bubbles of the BRICS countries. In this regard, we first detect positive and negative bubbles at short-, medium- and long-run for the stock markets of these emerging economies by using the multi-scale Log-Periodic Power Law Singularity (LPPLS) confidence indicator approach. Our findings revealed major crashes and rallies in the five stock markets over the period of 2nd week of February, 1999 to the 2nd week of September, 2020. Furthermore, we also observed similar timing of strong (positive and negative) LPPLS indicator values across the BRICS countries, suggesting commonality in the boom-bust cycles of these stock markets. In the second-step, we utilize impulse responses obtained from the local projection method (LPM) framework to capture the effect of US monetary policy shocks on a specific-type of bubble of a particular equity market of the BRICS bloc. Note that, we control for lagged values of the category of bubble under consideration of all the five countries, given the synchronous nature of movements in the bubble indicators within this group of countries. In general, the effect of US monetary policy shocks on the six bubble indicators for each country is limited, with strongest positive impact observed under the medium-term negative bubble indicator for Brazil, China and South Africa. Mildly negative evidence is also derived for China and South Africa when positive short- and long-term bubbles respectively, are considered.

With medium-term bubble indicators shown to lead long-term ones associated with deeper crashes and rallies, our results primarily imply that contractionary US monetary policy shocks can lead to deep downturns in the stock markets of Brazil, China and South Africa, before a recovery. Naturally, policymakers would need to respond in such a scenario by undertaking, possibly, expansionary fiscal policies to revive the domestic stock market, as reducing interest rates, associated with expansionary monetary policy, would lead to capital outflow, and prolong the downturn. But, if US monetary policies are expansionary, given our linear model, it could translate into a revival of the equity markets of Brazil, China and South Africa.

In light of the weak role of US monetary policy shocks, future research should be targeted at determining what possible local factors, including monetary policy,[9]

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[9]With strong evidence of monetary policy decisions in emerging markets moving in unison with that of the US (Iacoviello and Navarro, 2019), we do not expect to find a strong role of domestic

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of the BRICS be could impacting the domestic stock market bubbles. Furthermore, one could also delve into the role of global sentiment, i.e., a behavioral predictor (importance of which has been outlined by Pan et al. (2020)), in determining the high degree of synchroncity of the bubbles across the BRICS.[10]

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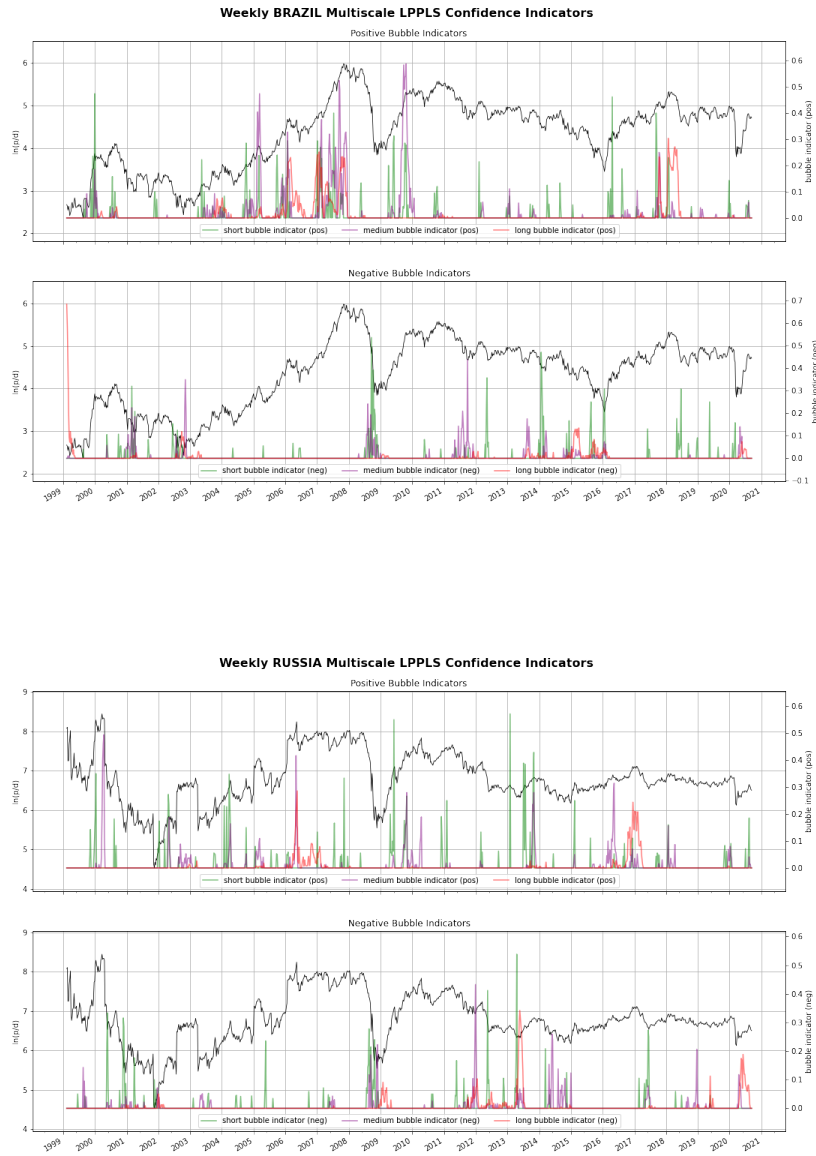monetary policies of the BRICS on individual-level equity market bubbles.

[10]An LPM-based analysis, not surprisingly, given the results of the individual countries, show insignificant effect of US monetary policy shocks on the TCIs, with complete details of these results available upon request from the authors.
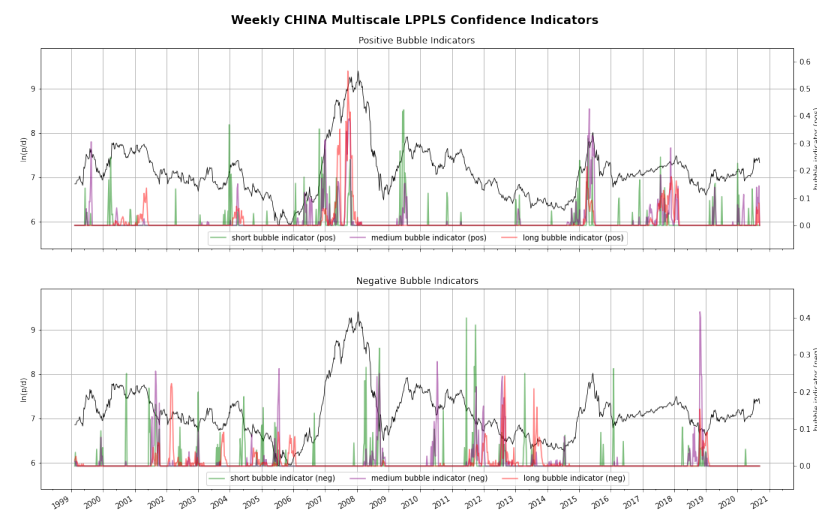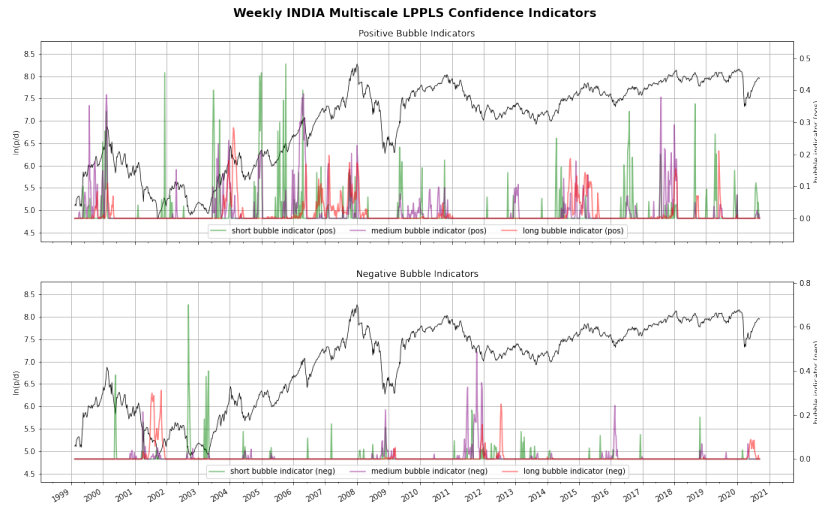
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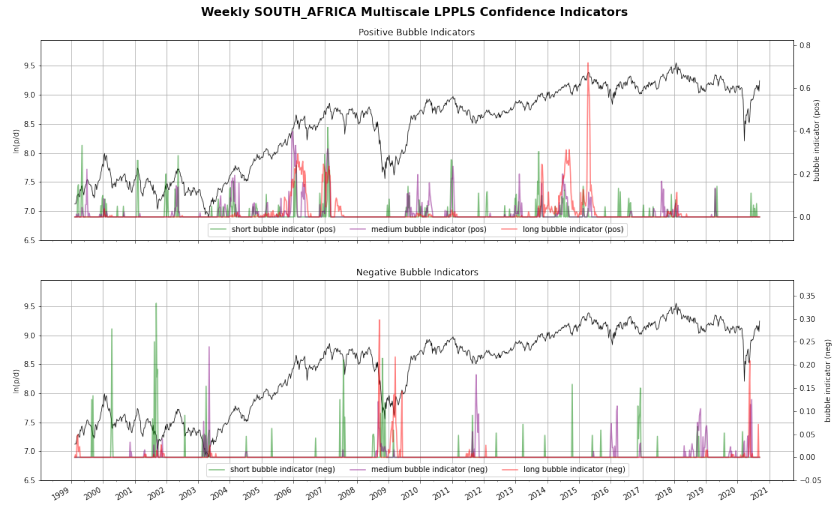
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Figures

Fig. 1: BRICS Weekly Multiscale LPPLS-CI and the US Monetary Policy Shock

Weekly INDIA Multiscale LPPLS Confidence Indicators

Positive Bubble Indicators

Negative Bubble Indicators

Weekly CHINA Multiscale LPPLS Confidence Indicators

Positive Bubble Indicators

Negative Bubble Indicators

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Weekly SOUTH_AFRICA Multiscale LPPLS Confidence Indicators

US Monetary Policy Shock (MP_t^{US})
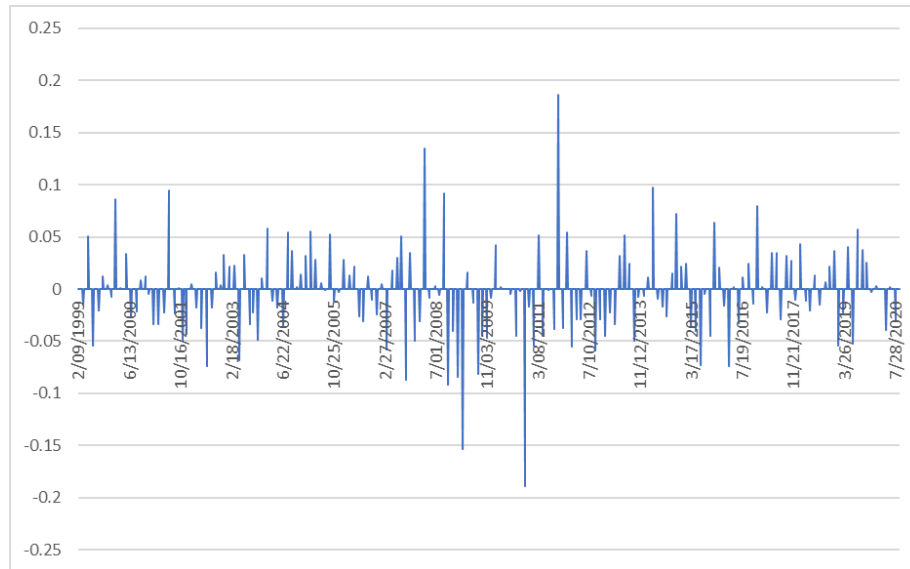
Fig. 2a: Impact of US Monetary Policy Shock on Short-Term Positive LPPLS-CIs
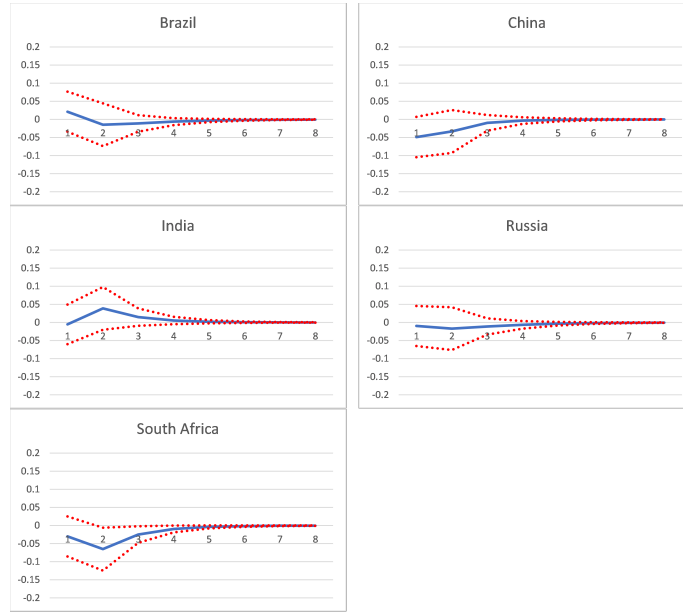
Fig. 2b: Impact of US Monetary Policy Shock on Short-Term Negative LPPLS-CIs

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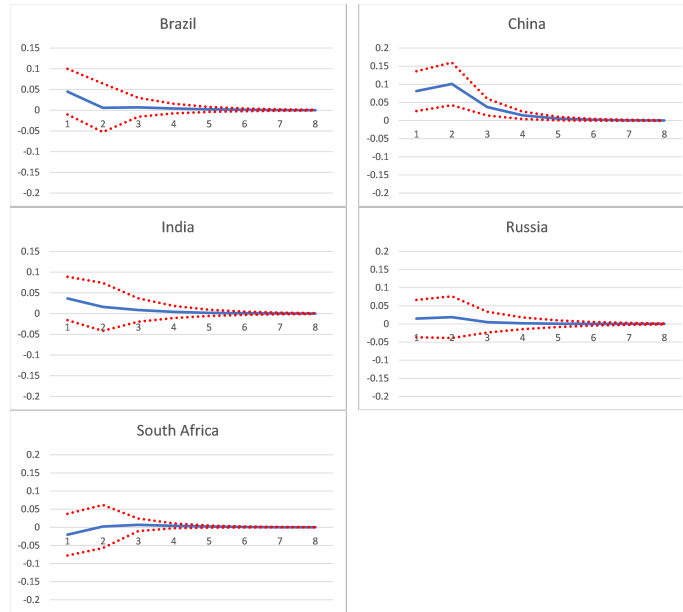
Fig. 2c: Impact of US Monetary Policy Shock on Medium-Term Positive LPPLS-CIs
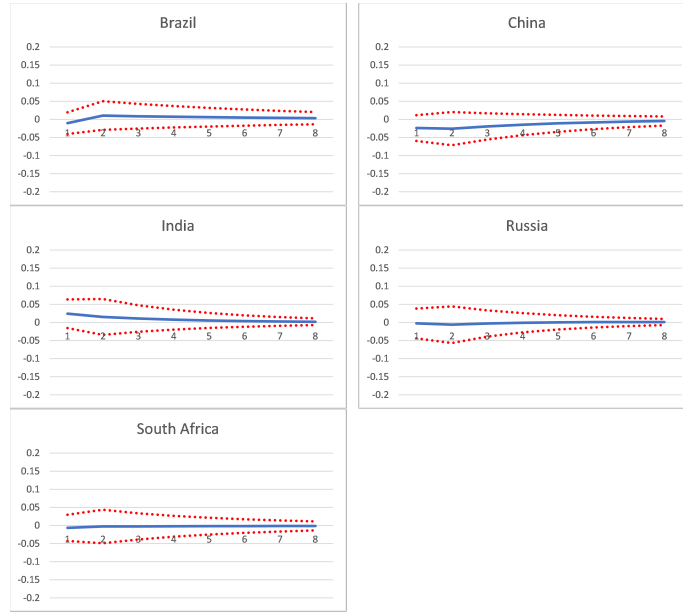
Fig. 2d: Impact of US Monetary Policy Shock on Medium-Term Negative LPPLS-CIs
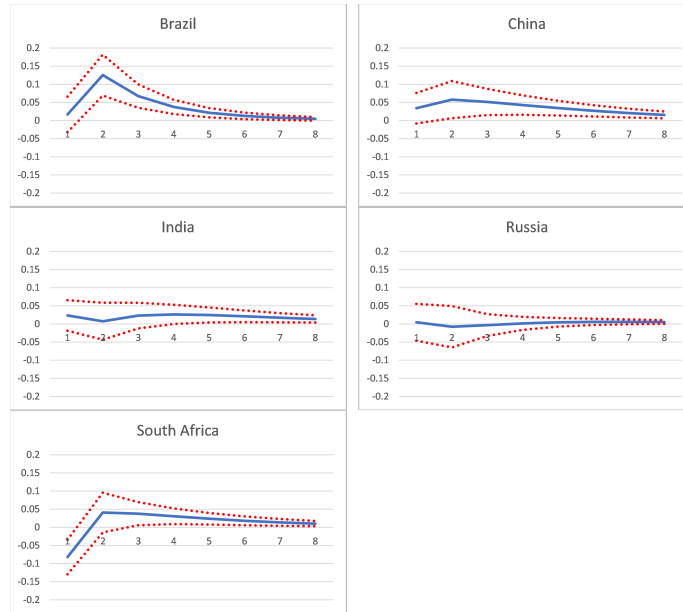
Fig. 2e: Impact of US Monetary Policy Shock on Long-Term Positive LPPLS-CIs
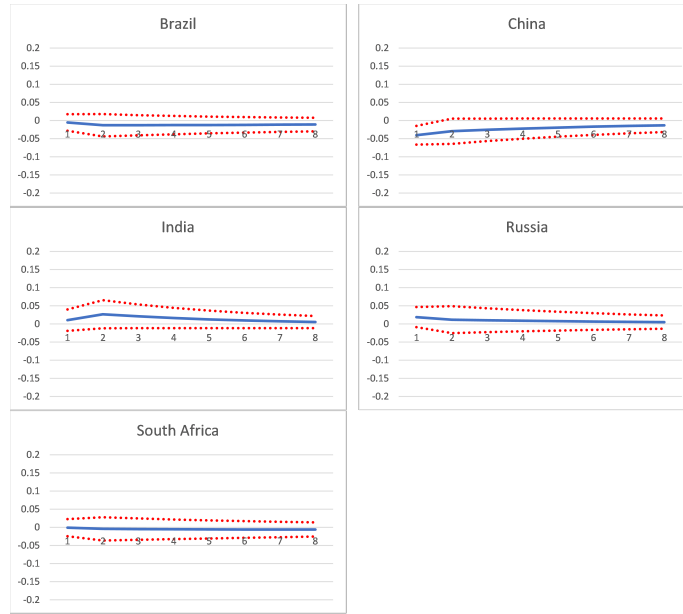
Fig. 2f: Impact of US Monetary Policy Shock on Long-Term Negative LPPLS-CIs
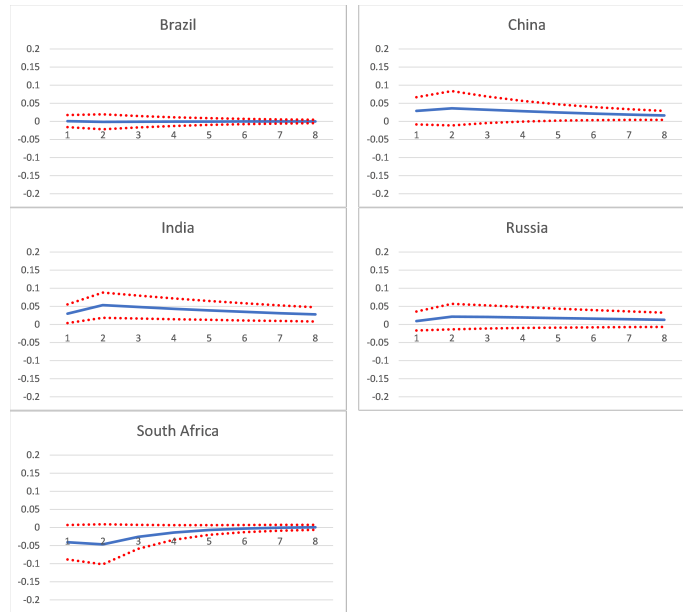
Note: Dotted red lines correspond to 95% confidence bands.

Appendix: Detecting Stock Market Bubbles

Given the LPPLS model as follows, we use the stable and robust calibration scheme developed by Filimonov and Sornette (2013):

$$E[\ln p(t)] = A + B(t_c - t)^m + C(t_c - t)^m \cos(\omega \ln (t_c - t)^m - \phi) \qquad \text{(A.2)}$$

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., log price-dividend ratio in our case) 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 so as 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:

$$E[\ln p(t)] = A + B(f) + C_1(g) + C_2(h), \qquad \text{(A.3)}$$

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:

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

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

$$F_1(t_c, m, \omega) = \min_{A,B,C_1,C_2} F(t_c, m, \omega, A, B, C_1, C_2) = F(t_c, m, \omega, \hat{A}, \hat{B}, \hat{C_1}, \hat{C_2}) \qquad \text{(4)}$$

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:

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

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

$$\{\hat{t}_c, \hat{m}, \hat{\omega}\} = \arg \min_{t_c,m,\omega} F_1(t_c, m, \omega). \tag{7}$$

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-CI, introduced by Sornette et al. (2015), is used to measure the sensitivity of bubble patterns in the log price-dividend ratio time series of each country. The larger the LPPLS-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 $B > 0$.

Following the work of Demirer et al. (2019), we incorporate bubbles of varying multiple time-scales into this analysis. We 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 manner, we obtain a weekly resolution from 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 $dt := t_2 - t_1 \in [90 : 300]$ trading days per

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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 $dt := t_2 - t_1 \in [300 : 745]$ 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

$$O = \frac{\omega}{2\pi} \ln \left(\frac{t_c - t_1}{t_c - t_2} \right),$$
$$D = \frac{m|B|}{\omega|C|}.$$

Fig. A1: Total Connectedness Indexes (TCIs)
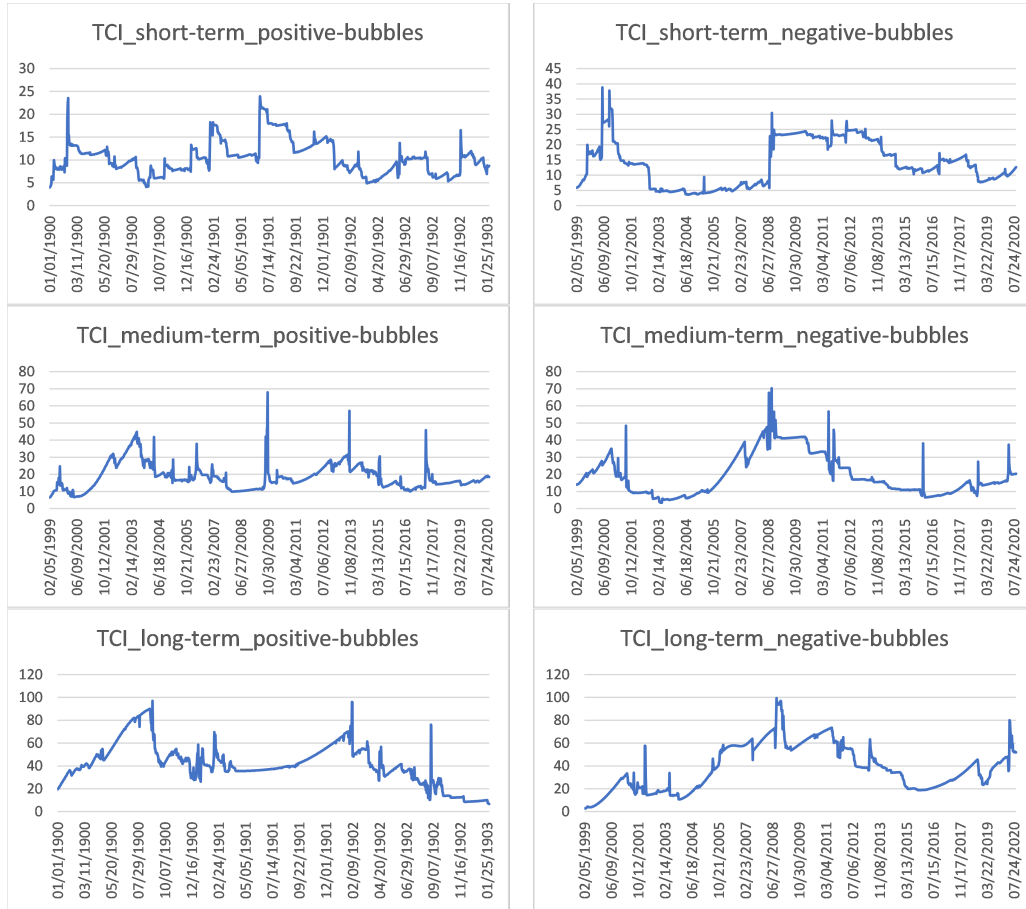
Note: The TCIs are derived from TVP-VARs comprising of a specific category of LPPLS-CIs of the BRICS.
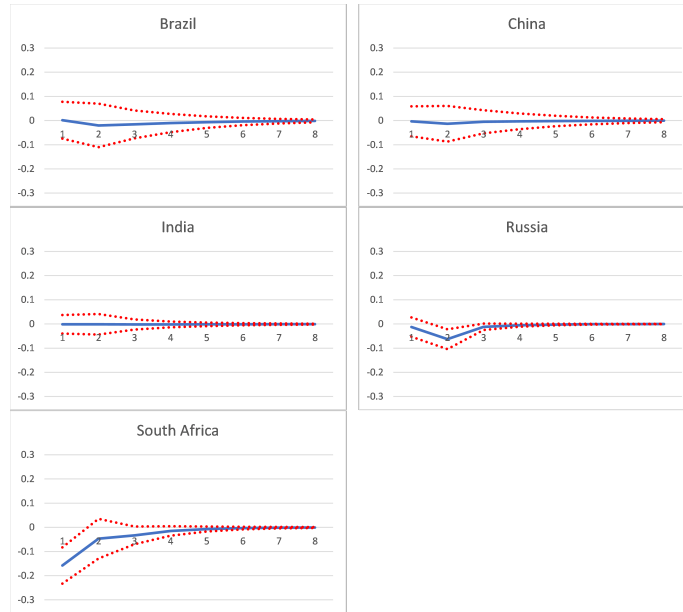
Fig. A2a: Impact of US Monetary Policy Shock on Short-Term Positive LPPLS-CIs (1999-2006)
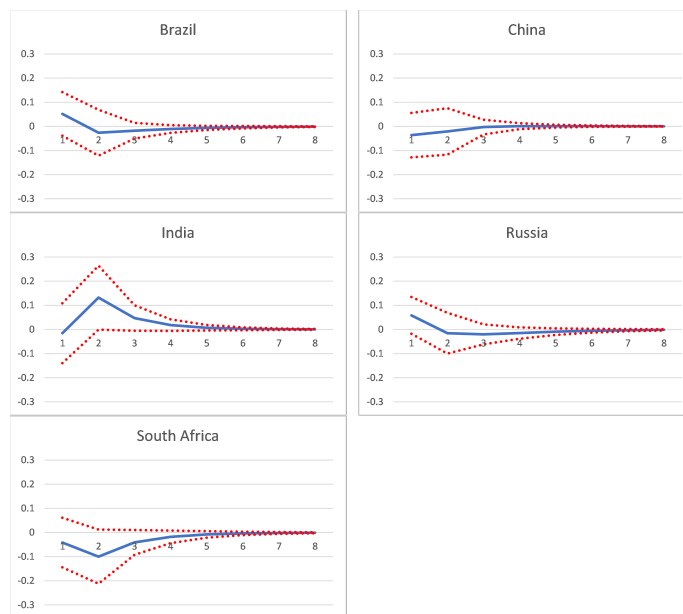
Fig. A2b: Impact of US Monetary Policy Shock on Short-Term Negative LPPLS-CIs (1999-2006)
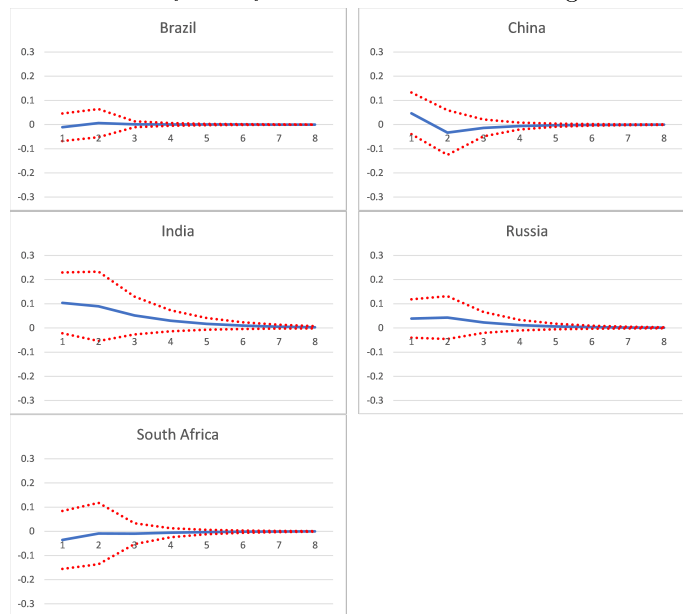
Fig. A2c: Impact of US Monetary Policy Shock on Medium-Term Positive LPPLS-CIs (1999-2006)
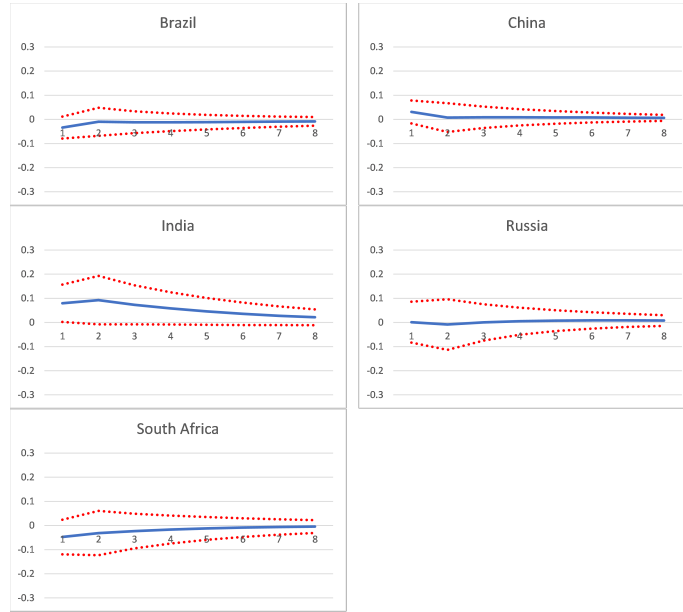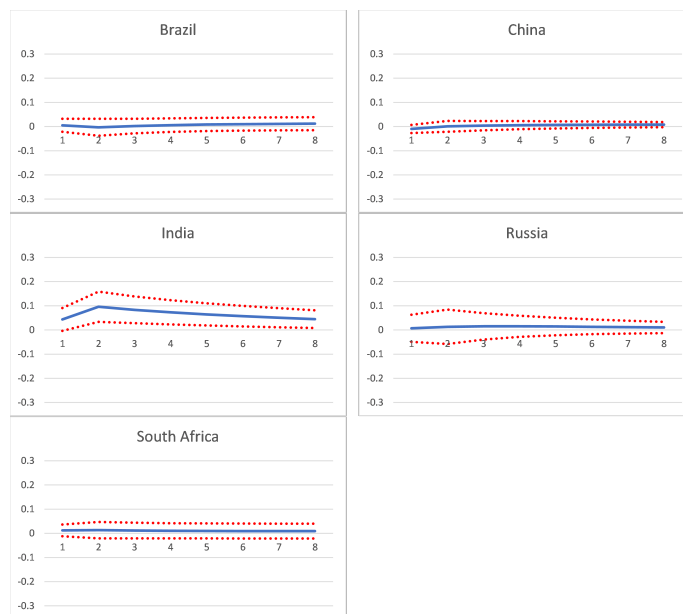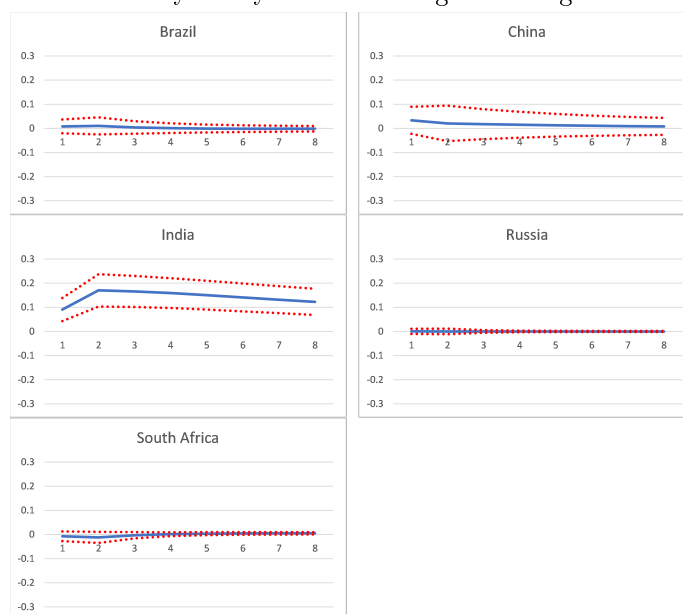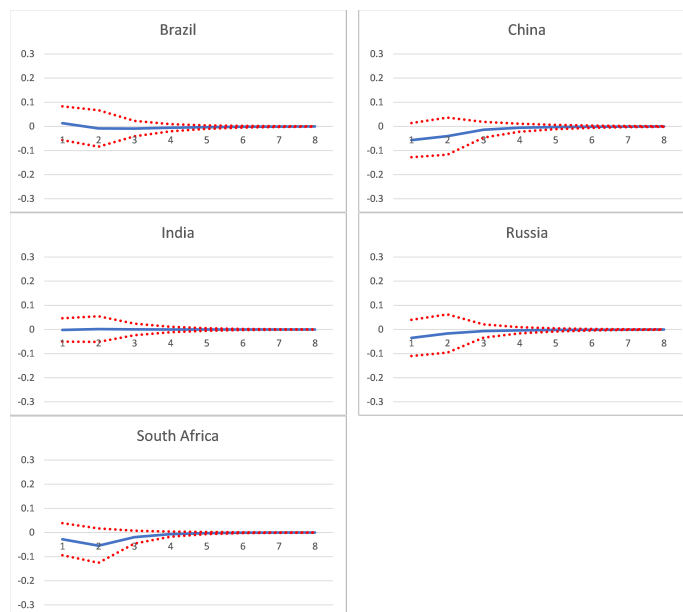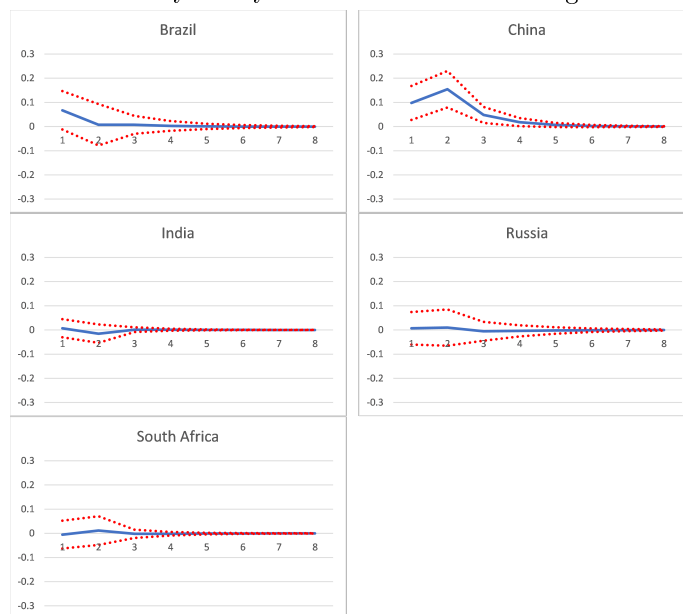

Fig. A2d: Impact of US Monetary Policy Shock on Medium-Term Negative LPPLS-CIs (1999-2006)

Fig. A2e: Impact of US Monetary Policy Shock on Long-Term Positive LPPLS-CIs (1999-2006)

Fig. A2f: Impact of US Monetary Policy Shock on Long-Term Negative LPPLS-CIs (1999-2006)

Note: Dotted red lines correspond to 95% confidence bands.

Fig. A3a: Impact of US Monetary Policy Shock on Short-Term Positive LPPLS-CIs (2007-2020)

Fig. A3b: Impact of US Monetary Policy Shock on Short-Term Negative LPPLS-CIs (2007-2020)

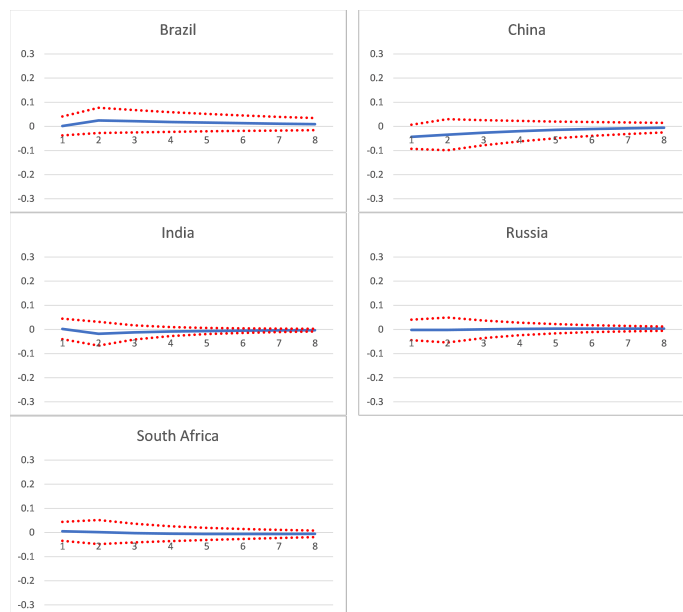Fig. A3c: Impact of US Monetary Policy Shock on Medium-Term Positive LPPLS-CIs (2007-2020)

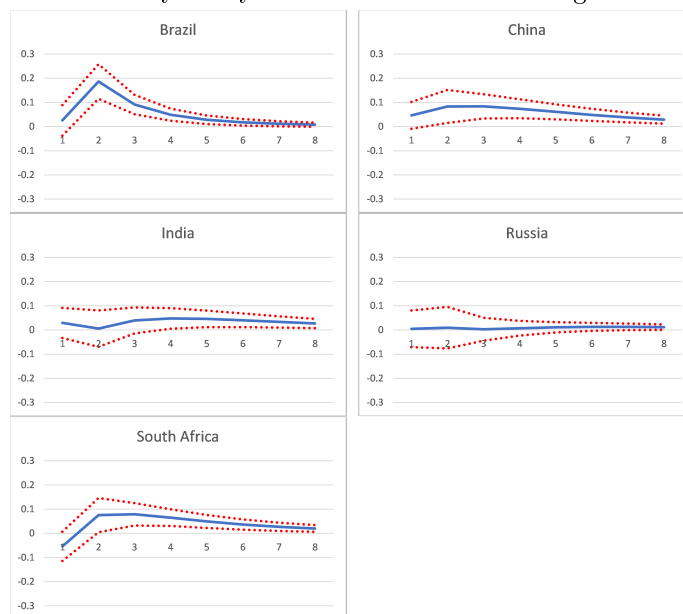Fig. A3d: Impact of US Monetary Policy Shock on Medium-Term Negative LPPLS-CIs (2007-2020)

Fig. A3e: Impact of US Monetary Policy Shock on Long-Term Positive LPPLS-CIs (2007-2020)
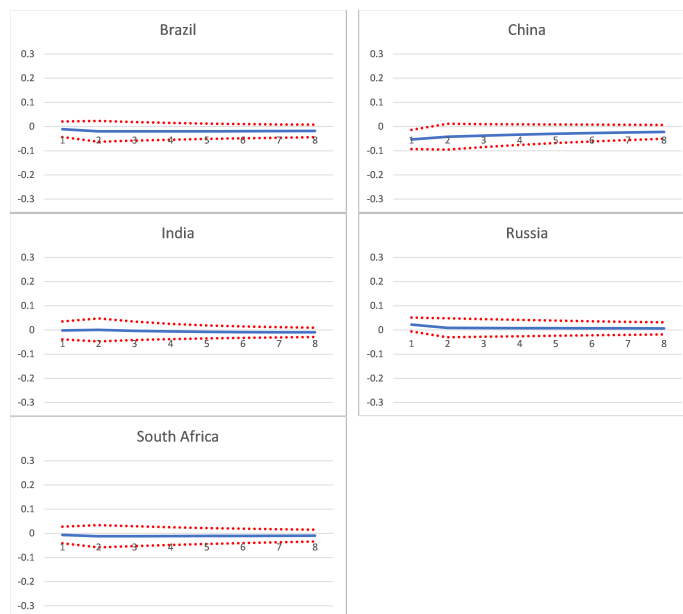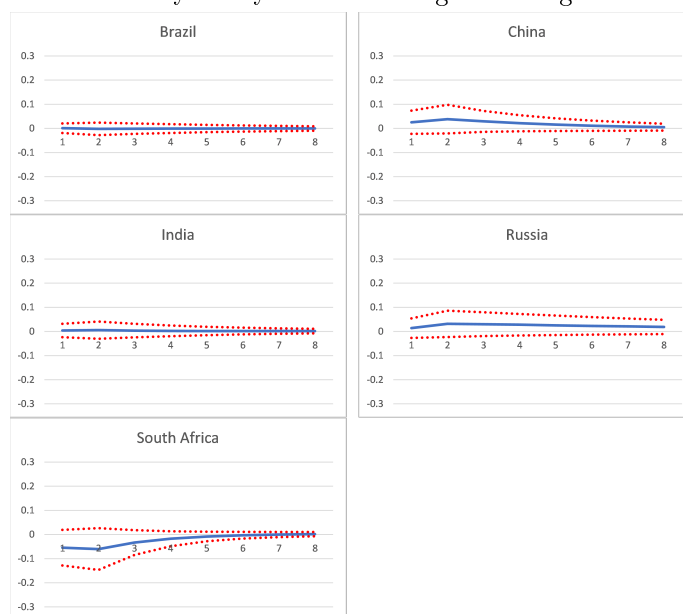

Fig. A3f: Impact of US Monetary Policy Shock on Long-Term Negative LPPLS-CIs (2007-2020)

Note: Dotted red lines correspond to 95% confidence bands.

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