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Modeling economic policy issues

Monetary policy and bubbles in G7 economies using a panel VAR approach: Implications for sustainable development

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ABSTRACT

We use the LPPLS Multi-Scale Confidence Indicator approach to detect both positive and negative bubbles in the short-, medium- and long-run for the stock markets of the G7 countries. We were able to detect major crashes and rallies in the seven stock markets over the monthly period of 1973:02 to 2020:09. We also observed similar timing of strong (positive and negative) LPPLS indicator values across the G7 countries, suggesting synchronized extreme movements in these stock markets. Given this, to obtain an overall picture of the G7, we used a panel VAR model to analyze the impact of monetary policy shocks on the six indicators of bubbles. We found that monetary policy not only impacts the bubble indicators but also responds to them, with the nature of the underlying responses contingent on whether bubbles are positive or negative in nature, as well as the time-scale we are analyzing. In light of these findings, our results have serious implications for monetary authorities of these advanced markets in terms of sustainable development, given the finance-growth nexus. But in general, we can conclude that central banks of the G7 can indeed "lean against the wind", and they have also been doing so under both conventional and unconventional monetary policy periods.

1. Introduction

There is a long-standing debate on whether and how monetary policy should respond to stock (asset) market bubbles (see, Caraiani and Călin, 2020a; Caraiani et al., 2021; André et al., 2022 for detailed literature reviews in this regard). The general perception is that stock (asset) price bubbles are difficult to detect and that monetary policy, specifically interest rate, is a blunt instrument to prick a bubble, which in turn is likely to result in unintended collateral damages. Given this, the consensus view is that central banks should focus on stabilizing inflation and the output gap only (Bernanke and Gertler, 1999, 2001). The Global Financial Crisis (GFC) has, however, challenged this line of thinking and has strengthened the opinion that monetary authorities should raise the interest rate to counteract stock (asset) price bubbles, even at the cost of temporarily deviating from their targets involving inflation or output gap. This is because, any losses associated with such deviations would be more than offset by the avoidance of the consequences of a future burst of the bubble in terms of sustainable development (Roubini, 2006; Mishkin, 2007). This line of reasoning has come to be known as

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"leaning against the wind". A central assumption associated with "leaning against the wind" is the belief that an increase in interest rates will reduce the size of a stock (an asset) price bubble (besides the stock (asset) price and/or returns itself). And herein lies the problem from an empirical standpoint, with studies obtaining contradictory evidence, i.e., monetary tightening may or may not necessarily translate into a decrease in the bubble component and/or overall stock prices (returns) (see, for example, Galí and Gambetti, 2015; Caraiani and Călin, 2018, 2020b; Paul, 2020; Çepni and Gupta, 2021; Çepni et al., 2021).

At this stage, it is important to get an understanding of the underlying contradictory theories that seem to provide the opposite empirical findings involving the impact of monetary policy on stock market bubbles. According to the discounted cash flow model (Fisher, 1930; Williams, 1938), stock prices are equal to the present value of expected future net cash flows. Theoretically then, monetary policy shocks are expected to affect stock prices by changing investors' expectation about future cash flows associated with economic activity, and by affecting the cost of capital, i.e., the real interest rate which is used to discount the future cash flows and/or the risk premium associated with holding stocks (Bernanke and Kuttner, 2005; Maio, 2014; Plakandaras et al., 2022). These two channels are, however, interlinked, given that a more restrictive monetary policy usually implies both higher discount rates and lower future cash flows. Thus, contractionary monetary policy shocks should be related to lower stock prices given the higher discount rate for the expected stream of cash flows and/or lower future economic activity. On the other hand, expansionary monetary policy shocks are commonly viewed as good news as these periods are usually associated with low interest rates, increases in economic activity, and higher earnings for the firms in the economy, and thus would imply higher stock prices. But more recently, Galí (2014) challenged the abovementioned conventional view that links interest rates and asset prices and their bubbles (see the theoretical exposition regarding this discussion in Appendix A of the paper). The reason is that, in the case of rational asset price bubbles, in equilibrium, the bubble component must grow at the rate of interest. Given this, an interest rate increase may end up enhancing the size of the bubble. Moreover, 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 have a negative impact on the price of an asset in periods where the bubble component is small compared to the fundamental. This is because an interest rate increase always reduces the "fundamental" price of the asset, which is an effect that should be dominant in "normal" times when the bubble component is small or non-existent. But 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 more than outweigh the negative impact on the fundamental component.

Against the backdrop of these conflicting theories, in this paper, we aim at providing comprehensive evidence with respect to the relationship between stock market bubbles and conventional and unconventional monetary policies involving the G7 (Canada, France, Germany, Italy, Japan, the United Kingdom (UK), and the United States (US)) countries over the monthly period of 1973:02 to 2020:09. In this regard, the choice of G7 countries was driven by the availability of reliable stock and macroeconomic data, particularly an uniform metric of conventional and unconventional monetary policies as captured by the Shadow Short Rate (SSR) (Wu and Xia, 2016), spanning nearly half a century.[1] As far as detecting bubbles are concerned, we not only use the Log-Periodic Power Law Singularity (LPPLS) model, originally developed by Johansen et al. (1999, 2000) and 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 of Demirer et al. (2019) to characterize 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 al., 2018 for detailed reviews). We consider this important since this would allow us to gauge the possible asymmetric nexus between monetary policy and equity market bubbles, given that crash and recovery at different horizons can carry different information on economic agents and central banks. Once we have identified the bubbles, we then rely on a Panel Vector Autoregressive (PVAR) model to analyze the impact of a monetary policy shock on the six (positive and negative for short-, medium-, and long-runs) different indicators of equity market bubbles (and also the feedback from the bubbles on to the movements of the interest rates). The decision to rely on a PVAR model was motivated by the high degree of synchronization of the indicators of the bubbles (which we discuss in detail below, with some evidence in terms of speculation in financial markets being detected by Demirer et al., 2021), besides the well-established evidence of the same involving output, inflation and monetary policy decisions of advanced (including G7) economies (Antonakakis, 2012; Antonakakis et al., 2019; Szafranek, 2021).

In light of this, our paper differs from existing studies on this topic, which primarily focuses on the US or a set of the Organisation for Economic Co-operation and Development (OECD) countries considered independently in a time series set-up, that tends to ignore interrelationships between the variables across the G7 economies while accounting for short-, medium-, and long-term positive and negative bubbles and the monetary policy nexus, in the process of outlining possible asymmetry in these relationships. Hence, to the best of our knowledge, this is the first paper to analyze the interaction between multi-scale positive and negative bubbles and conventional and unconventional monetary policies in the G7 countries based on a PVAR model. The remainder of the paper is organized as follows: Section 2 discusses the

[1] But the G7 were chosen also because this group of countries account for nearly two-thirds of global net wealth and nearly half of world output, and hence, their monetary policy decisions and (extreme) movements in stock markets, as well as associated macroeconomic impacts, are likely to have a worldwide spillover effect and impact the sustainability of the economic system (Das et al., 2019).

methodologies associated with the multi-scale LPPLS and PVAR models, then Section 3 presents the data and the empirical findings involving the detection of the bubbles, as well as the effects of monetary policy shocks on the detected bubbles, and the feedback, i.e., the impact of shocks to the bubble indicators on to the interest rates. Finally, Section 4 concludes the paper.

2. Econometric framework

We combine two econometric methods in a two-step procedure. First, we extract multi-scale LPPLS Confidence Indicators associated with positive and negative bubbles, at the three time-scales of short-, medium-, and long-run. Second, we build a PVAR featuring the G7 economies' output growth, inflation, changes in interest rates and one out of the six metric of bubbles that is common across the seven countries.

2.1. Detecting stock market bubbles

2.1.1. The LPPLS model

Given the LPPLS model as follows, we use 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 price of the observed time-series 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), Eq. (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

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

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 Eq. (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:

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

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

$$F_1(t_c, m, \omega) = \min_{A,B,C_1,C_2} F(t_c, m, \omega, A, B, C_1, C_2) = F(t_c, m, \omega, \hat{A}, \hat{B}, \hat{C}_1, \hat{C}_2) \tag{4}$$

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:

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

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 $\{t_c, m, \omega\}$.

2.1.2. LPPLS multi-scale confidence indicator

The LPPLS confidence indicator, 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 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 $B > 0$.

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 $dt := t_2 - t_1 \in [30 : 90]$ 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. The PVAR model

We present below the key elements of the PVAR approach that we use. This follows the approach in Canova and Ciccarelli (2013) as well as Dieppe et al. (2016).[2] A PVAR consists of N entities, i.e., the seven countries in our application. For each entity or unit, there is a number of n endogenous variables, a p number of lags (which we set at 12, given ample evidence that monetary policy takes a year to impact the economy Walsh, 2017) as well as a sample of T periods. In our case, the data is balanced. We consider here the pooled estimator which relaxes all key assumptions regarding the PVAR, and the remaining panel characteristic is basically that the data is coming from different entities. Given this, the PVAR can be formally written as:

$$\begin{bmatrix} y_{1,t} \\ y_{2,t} \\ \dots \\ y_{N,t} \end{bmatrix} = \begin{bmatrix} A^1 & 0 & \dots. & 0 \\ 0 & A^1 & \dots. & 0 \\ \dots & & & \\ 0 & 0 & \dots. & A^1 \end{bmatrix} \begin{bmatrix} y_{1,t} \\ y_{2,t} \\ \dots \\ y_{N,t} \end{bmatrix} + \dots + \begin{bmatrix} A^p & 0 & \dots. & 0 \\ 0 & A^p & \dots. & 0 \\ \dots & & & \\ 0 & 0 & \dots. & A^p \end{bmatrix} \begin{bmatrix} y_{1,t} \\ y_{2,t} \\ \dots \\ y_{N,t} \end{bmatrix} + \begin{bmatrix} \epsilon_{1,t} \\ \epsilon_{2,t} \\ \dots \\ \epsilon_{N,t} \end{bmatrix}$$

In this case, we have $\Sigma_{ii,t} = E(\epsilon_{i,t}, \epsilon'_{i,t}) = \Sigma_c$ for all i, and $E(\epsilon_{i,t}, \epsilon'_{j,t}) = 0$. Here c indicates that the value does not vary in time and that it is the same for all units.

We can further write this more compactly, as follows:

$$\begin{bmatrix} y'_{1,t} \\ y'_{2,t} \\ \dots \\ y'_{N,t} \end{bmatrix} = \begin{bmatrix} y'_{1,t-1} & \dots & y'_{1,t-p} & x'_t \\ y'_{2,t-1} & \dots & y'_{2,t-p} & x'_t \\ \dots & & & \\ y'_{N,t-1} & \dots & y'_{N,t-p} & x'_t \end{bmatrix} \begin{bmatrix} (A^1) \\ \dots \\ (A^p) \\ C \end{bmatrix} + \begin{bmatrix} \epsilon'_{1,t} \\ \epsilon'_{2,t} \\ \dots \\ \epsilon'_{N,t} \end{bmatrix}$$

[2] The PVAR estimations are obtained using the Bayesian Estimation, Analysis and Regression (BEAR) toolbox, as developed by Dieppe et al. (2016), and is available for download from: https://github.com/european-central-bank/BEAR-toolbox.

This can be written formally as:

$$Y_t = X_t B + \epsilon_t \tag{8}$$

After stacking over the T observations, we get:

$$Y = XB + \epsilon \tag{9}$$

We can re-write the model using a vectorized notation as follows:

$$vec(Y) = (I_n \bigotimes X) vec(B) + vec(\epsilon) \tag{10}$$

resulting in the following specification:

$$y = \bar{X}\beta + \epsilon \tag{11}$$

In this case, the errors have a normal distribution with $\epsilon \sim N(0, \bar{\Sigma})$ and $\bar{\Sigma} = \Sigma_c \bigotimes I_{NT}$.

We perform a Bayesian estimation of the PVAR model based on the normal-Wishart prior specification. This prior improves over the standard Minnesota prior by considering that the residual covariance matrix $\bar{\Sigma}$ is not known. Thus, when estimating the PVAR with this prior, both β and $\bar{\Sigma}$ are considered unknowns.[3]

3. Data

We first obtain weekly bubble indicators, with them derived based on the natural logarithmic values of the daily dividend-price ratio of the seven countries, using the dividend and the stock price index series, in their local currencies, obtained from Refinitiv Datastream. The generated bubbles indicators cover the weekly period of the 1st week of (7th) January, 1973 to 2nd week of (13th) September, 2020. Since, our macroeconomic variables are at a monthly frequency, to obtain a monthly value for each multi-scale confidence indicators, we take the average for each of the scales' weekly values that fall within a given month. As far as the macroeconomic controls were concerned, we used month-on-month growth of industrial production, month-month Consumer Price Index (CPI)-based inflation rate, and change in the interest rate, with all transformations to the data ensuring stationarity of the variables under consideration. As far as the interest rate variable is concerned, note that we use the three-month money market interest rates, merged with the SSR of the individual countries (of course from 1999 onwards France, Germany, and Italy have the same values) from the time the latter became available. Industrial production, CPI and the money market interest rates were all sourced from the Main Economic Indicators database of the OECD.[4] Specifically speaking, barring the US, which begins in 1985:11, the SSRs of the remaining six countries are available from 1995:01. The SSRs are derived from the website of Dr. Leo Krippner.[5]

Note that, the SSR estimates used in this paper are derived from the works of Krippner (2013, 2015), due to their coverage involving the G7, besides being considered an improvement over those obtained by Wu and Xia (2016) (for the Euro area, the UK and the US), as discussed in detail by Krippner (2020). The SSR is based on models of the term-structure, which essentially removes the effect that the option to invest in physical currency (at an interest rate of zero) has on yield curves, resulting in a hypothetical "shadow yield curve" that would exist if the physical currency were not available. The "shadow policy rate" generated in this manner, therefore, provides a measure of the monetary policy stance after the actual policy rate reaches zero. The main advantage of the SSR is that it is not constrained by the Zero Lower Bound (ZLB), and thus allows us to combine the data from the ZLB period with that of the non-ZLB era, and in turn to use it as the common metric of monetary policy stance across the conventional and unconventional monetary policy episodes. Ultimately, our monthly period of analysis covers 1973:02 to 2020:09, with the variables being output growth, inflation, monetary policy and a specific bubble indicator. It must be emphasized that the choice of these variables is in line with the literature on monetary VARs that is augmented with (moments of) asset prices, with the reader is referred to the studies cited above for further details.

4. Empirical findings

We start off by discussing each scale of the Multi-Scale LPPLS-CI values for G7 countries, and then the impact of monetary policy shocks on these indicators and vice versa in a PVAR model.

3 As a robustness check, we also estimated the PVAR model via a classical Ordinary Least Squares (OLS) approach by utilizing the Pooled Mean Group (PMG) estimator. While, the sign of the impact of the shocks were similar to those reported below in Section 4.2, the derived responses from the PVAR model was exceptionally unstable to help us draw reliable inferences. These results are available upon request from the authors, and highlights the superiority of using a Bayesian estimation to tackle any possible issue involving overparameterization of the PVAR associated with the usage of a large lage-length.

4 https://www.oecd.org/sdd/oecdmaineconomicindicatorsmei.htm.

5 https://www.ljkmfa.com/.

4.1. Identification of bubbles in the G7 countries

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. Higher LPPLS-CI values from a corresponding scale indicate the LPPLS signature is present for many of the fitting windows to which the model was calibrated. As such, it is more reliable. From a brief visual inspection of the plots in Fig. 1, we find that there are many spikes in the LPPLS-CI values preceding regime shifts in the underlying log price-to-dividend ratio.

As previously stated in Section 2.1.2, the long-term positive LPPLS-CI (red lines in Fig. 1) is comprised of 223 single LPPLS model fits spanning fitting windows of size 300 to 745 observations. This represents nearly 3 years of data. Due to the larger calibration time-period we anticipate that large indicator values will occur less frequently at this scale than they would for smaller scales. We see 4 strong positive long-term LPPLS-CI values. The first is observed in Canada, France, Germany, Italy, the UK, and the US from 1973 to 1974. This strong indicator value preceded one of the worst global market downturns since the "Great Depression" lasting from 1973:01 through 1974:12. This crash came on the heels of the collapse of the Bretton Woods system, and the dollar devaluation from the Smithsonian Agreement. Next, we see a strong positive long-term LPPLS-CI value preceding "Black Monday" in 1987:10 in Canada, Japan, the UK and the US. For the UK, the LPPLS-CI value recorded prior to "Black Monday" is the largest in the dataset. A similar observation for Canada, the UK, and the US, as well as to some extent for Germany, can be made during the Asian Financial Crisis of 1997. We also see a clustering of highly positive LPPLS-CI values leading up to the Dot-com bubble burst over 2000:03 to 2002:10, especially for Canada, France, Italy, the UK, and the US, but immediately following the crash, we see strong negative LPPLS-CI values, which in turn, signal rallies in these countries. While not so much for the positive LPPLS-CIs, there are strong negative LPPLS-CI values for all G7 constituents except the US following the GFC, suggesting faster stock market recoveries in the remaining six countries.

The medium-term LPPLS-CI (purple lines in Fig. 1) uses 105 fits and spans fitting windows of size 90 to 300 observations. This represents a little over one year of data. In general, we observed pronounced LPPLS-CI values (positive and negative) at points where we detected the same for the long-term indicators. In addition, we found that strong positive medium-term LPPLS-CI values were formed before strong long-term LPPLS-CI values leading up to the GFC.

The short-term LPPLS-CI (green lines in Fig. 1) uses 30 fits from fitting windows of size 30 to 90 observations. This represents just 1 month. As can be seen from Fig. 1, this scale produces the most signals. It can also be inferred from the figure that the smallest crashes/rallies are signaled from this scale, possibly due it picking up idiosyncratic signals. However, we still can see small corrections immediately following a strong short-term LPPLS-CI value. It is also interesting to notice, just as with the medium-term indicators preceding the long-term indicators, the short-term indicators tend to lead the medium-term ones, in the context of the major bubble dates identified by the medium- and long-run indicators discussed above. This adds support to the finding from Demirer et al. (2019) that the maturation of the bubble towards instability is present across several distinct time-scales.

Given that an asset's volatility increases with the square root of time as the latter increases, we can conclude that shorter time-scales are best-suited for detecting smaller crashes or rallies, while longer time-scales are best-suited for detecting larger crashes or rallies. This intuition is confirmed by empirically observing the results from Fig. 1, whereby long-term scales produce fewer signals but appear to capture larger crashes or rallies, and the shorter-scales generate more signals that precede smaller crashes or rallies. We also observed similar timing of strong (positive and negative) LPPLS-CI values across the G7, lending to the idea of synchronized boom and bust cycles of the seven developed equity markets, and hence motivating the use of a PVAR to analyze the impact of monetary policy shocks on bubbles (and the reverse), to get an overall understanding. Overall, these empirical findings support the claim made in the introduction that the LPPLS framework is a flexible tool for detecting positive and negative bubbles across different time-scales. Note that, besides the crises episodes discussed above, these indicators in general also show spikes associated with crashes and recoveries before and around the European sovereign debt crisis from 2009 to 2012, the "Brexit" in 2016, and to some extent COVID-19 as well, especially for the US involving the positive bubble indicator.

4.2. Monetary policy and bubbles

The impulse response functions (IRFs) are identified using a Cholesky decomposition, with the variables ordered in accordance with the monetary policy-stock market interaction literature discussed in the introduction. More specifically, output growth is followed by the inflation rate, then the change in the interest rate, and finally one of the six multi-scale LPPLS-CI. This implies that monetary policy shocks will have an immediate effect on the bubbles, with the stock market being a fast-moving variable, while output growth and inflation are impacted with a delay, as these variables are related to the real economy. Our focus is the impact of monetary policy shocks on the bubble indicators, as well as the possible response of monetary policy to a shock in the bubble indicator. The median impulse responses, with 68% confidence bands, following a one standard deviation shock, are presented in Fig. 2. Given the evidence in favor of comovements of the variables in our system, the usage of a PVAR provides the so-called "average" impact across the seven economies, besides robust statistical inferences, as now we have more than 4000 observations to work with, in a panel set-up.[6] Note

[6] Of course, country-specific analysis, possibly as well as with time-variation, could be an area(s) of future research.

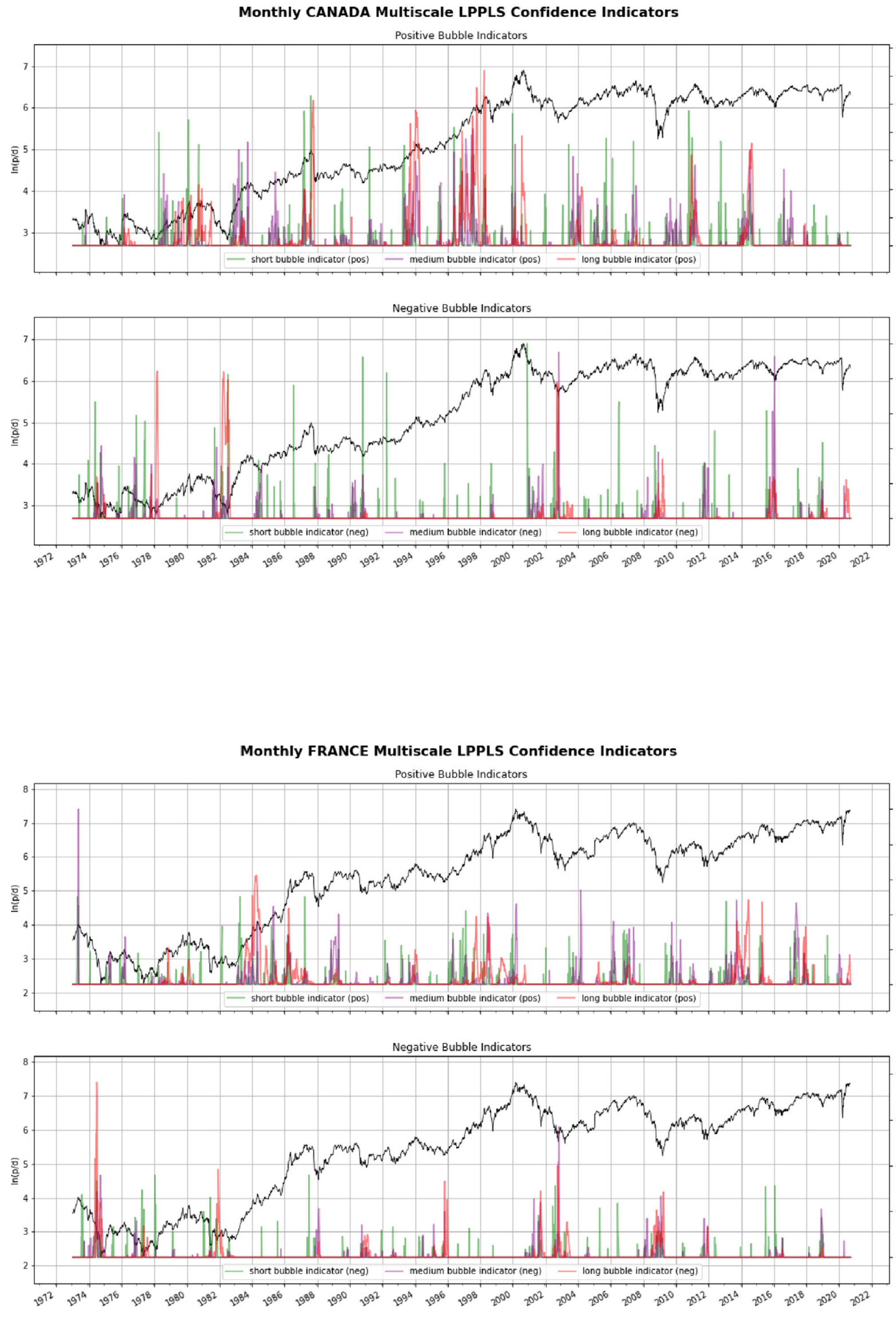
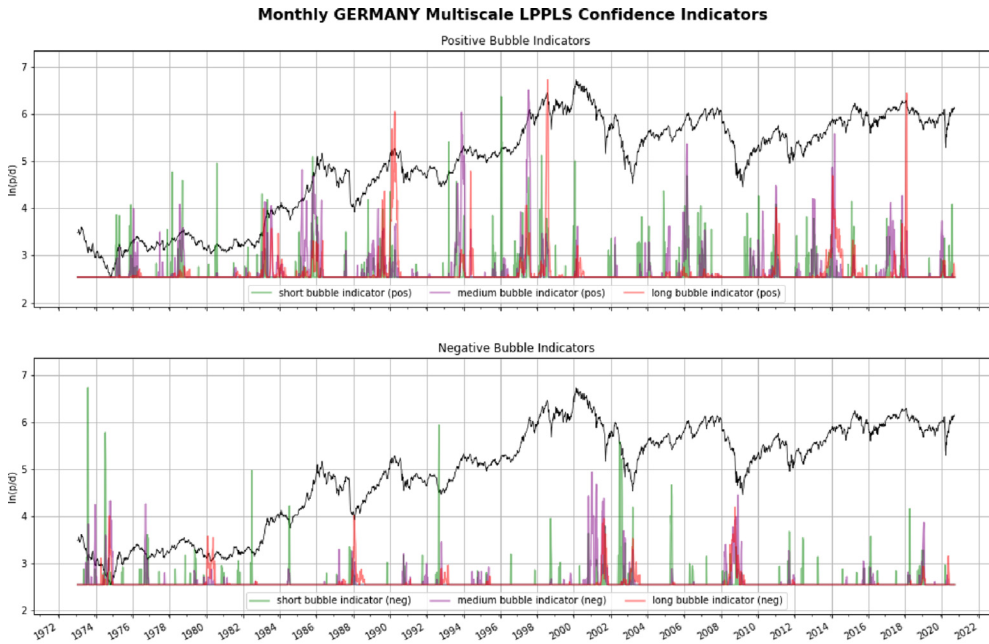


Fig. 1. G7 monthly mulit-scale LPPLS-CI.



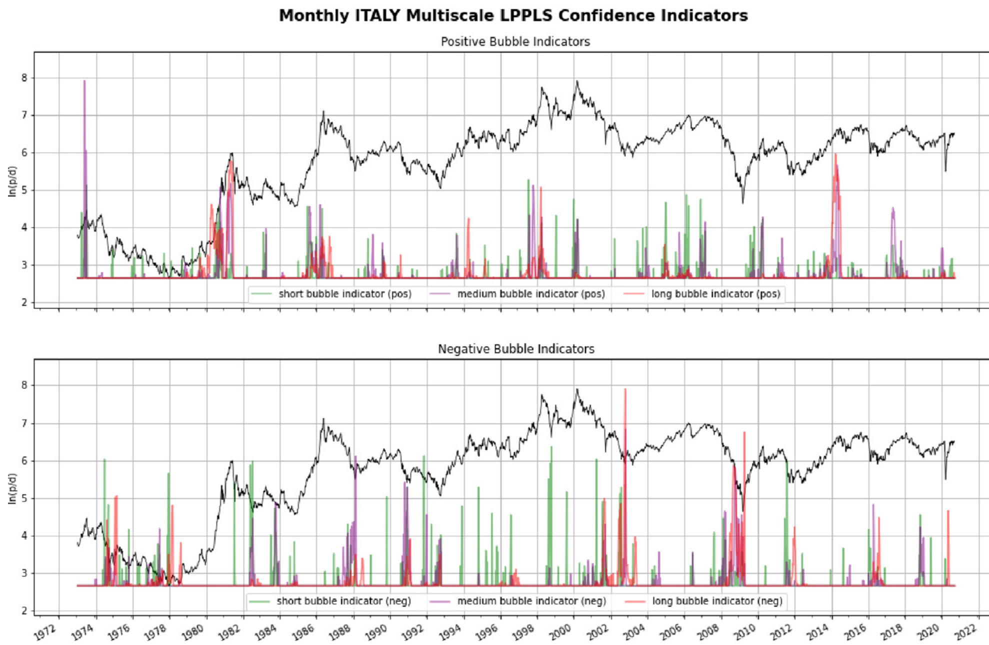
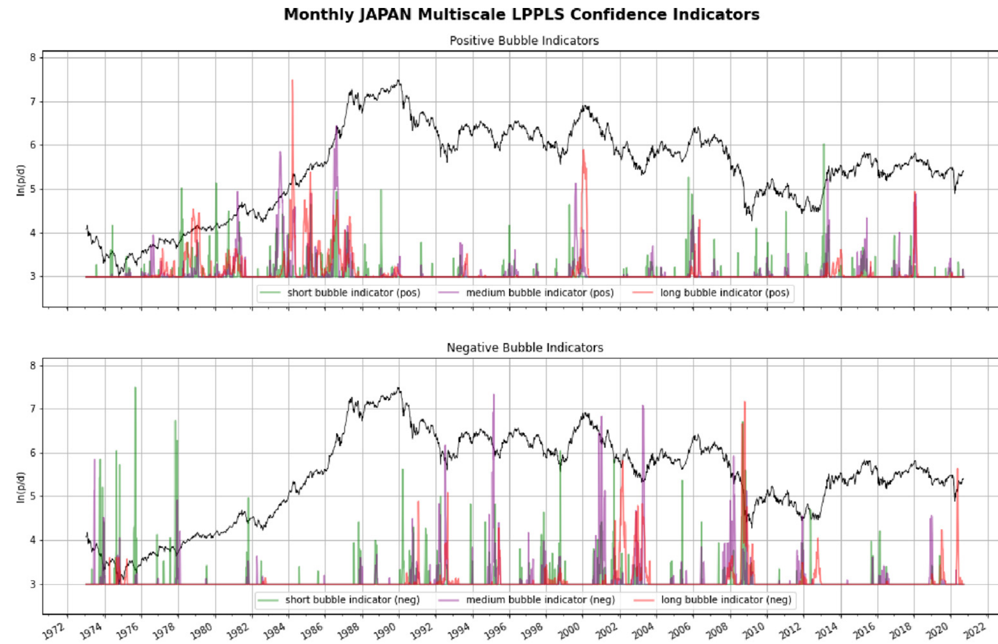


Fig. 1. (*continued*).



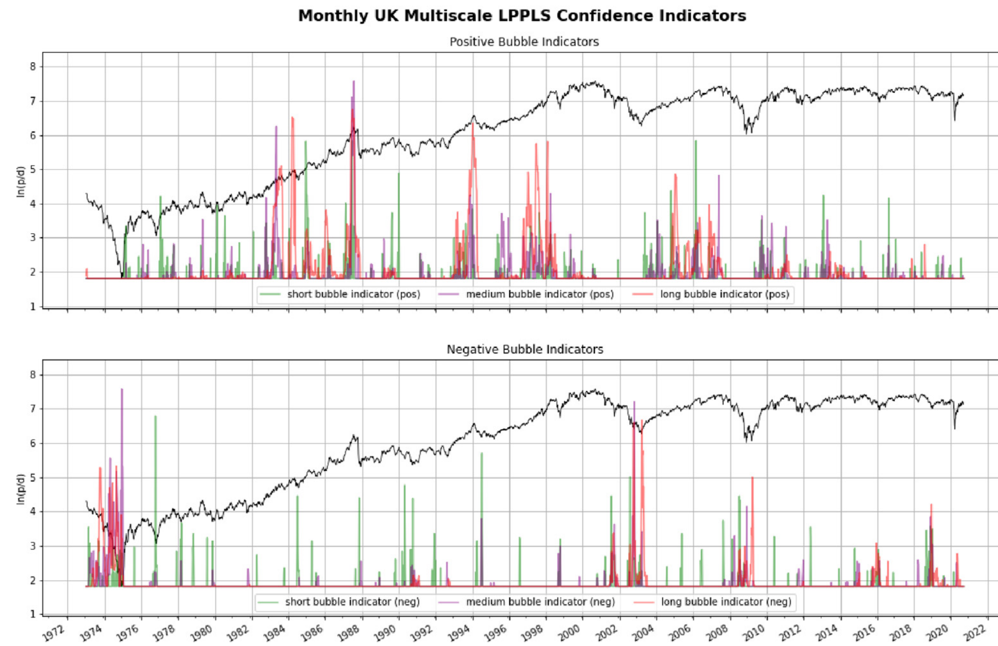


Fig. 1. (*continued*).

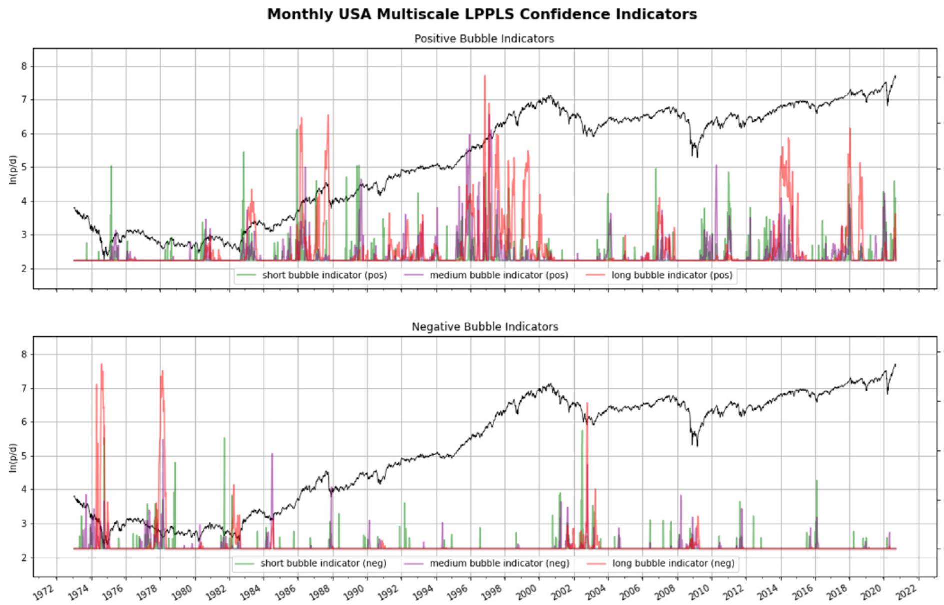


Fig. 1. (*continued*).

that, as is usual with small-scale monetary VAR models, there is evidence of both the output and price puzzles. Now, we turn our attention to the monetary policy-bubbles nexus.

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.[7] As can be seen from (the 4th row and 3rd column of) Figs. 2(a), 2(c), and 2(e), the impact of a monetary policy shock has a significant negative impact on the positive medium- and short-term bubble indicators, with the effect being insignificant for the long-term indicator, and slightly delayed for the medium-term indicator, but is similarly strong in comparison with the short-term case (when we compare the highest response (in absolute terms) of the impulses). The effect persists for about half a year. More importantly, this result is in line with the conventional discounted cash flow theory that monetary policy would have a negative impact on stock prices. Again in support of this theory, as observed from (the 4th row and 3rd column of) Figs. 2(b), 2(d), and 2(f), a contractionary monetary policy is found to increase the negative bubble indicator in a statistically significant manner across all the time-scales over at least six months, which is basically capturing a fall in stock prices before it starts rallying. As with the positive indicators, the monetary policy effect is delayed in the medium-term. The strongest effect is observed for the long-term indicator, followed by the short and medium-term, in terms of the peak of the impulse response functions.

Overall, there is some degree of asymmetry in terms of how monetary policy impacts the long-term positive and negative bubble indicators, with no significant impact under the former, as is the strength of the impact within each category across the 3 time-scales. Furthermore, barring the case of the long-term positive indicator of bubbles, positive bubble indicators are more strongly affected in the absolute sense than negative indicators. In other words, a contractionary monetary policy can prick a positive bubble more effectively than the revival of the stock market via an expansionary monetary policy, particularly in the medium- and short-run. Recall that the longer time-scales are best-suited for detecting larger crashes or rallies, but also short- and medium-term indicators precede the long-term indicators. In light of this, the fact that monetary shock tends to impact the short- and medium-run bubbles indicators, particularly the former, in the strongest manner, contractionary policy decisions seem to be well-equipped to prevent crashes in a timely manner. At the same time, expansionary monetary policy decisions can also recover the stock market by strongly influencing all the time-scale indicators, and particularly the long-run bubbles indicator. In other words, in this case, when

7 Given this, as part of a preliminary analysis to obtain an overall picture, we first estimated seven Dynamic Factor Models (DFMs), following Jackson et al. (2016), involving the six indicators and the month-on-month changes of the monetary policy instrument for the G7 countries, and derived the corresponding six common (global) factors associated with the bubble indicators, and one for the changes in the interest rates. Then we utilized the Quantile-on-Quantile regression approach of Sim and Zhou (2015), whereby we regressed the common factors of the bubbles indicators on the same of the interest rate. As can be seen from Figs. C.1(a)–C.1(f) in Appendix C of the paper, monetary policy generally positively impacts the negative bubbles factors, while the effect is basically negative for the positive bubbles factors, over the respective distributions of the dependent and the independent variables, corresponding to their various states. These findings are in line with intuition and the conventional theory as explained in detail in the text associated with the discussion of the results from the PVARs.

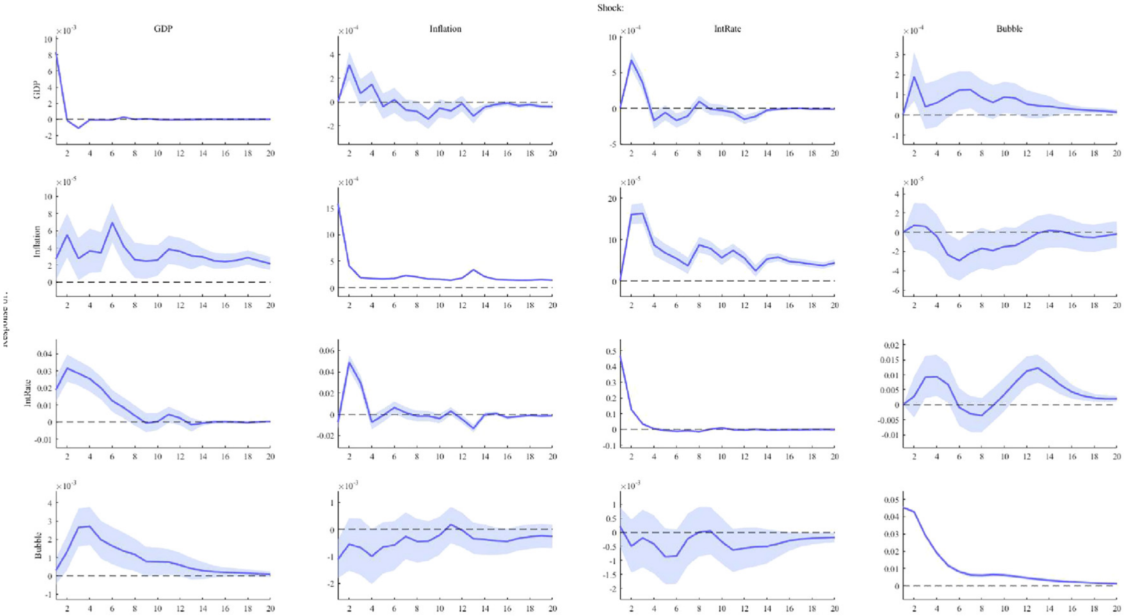


Fig. 2(a). PVAR results with long-term positive bubble.

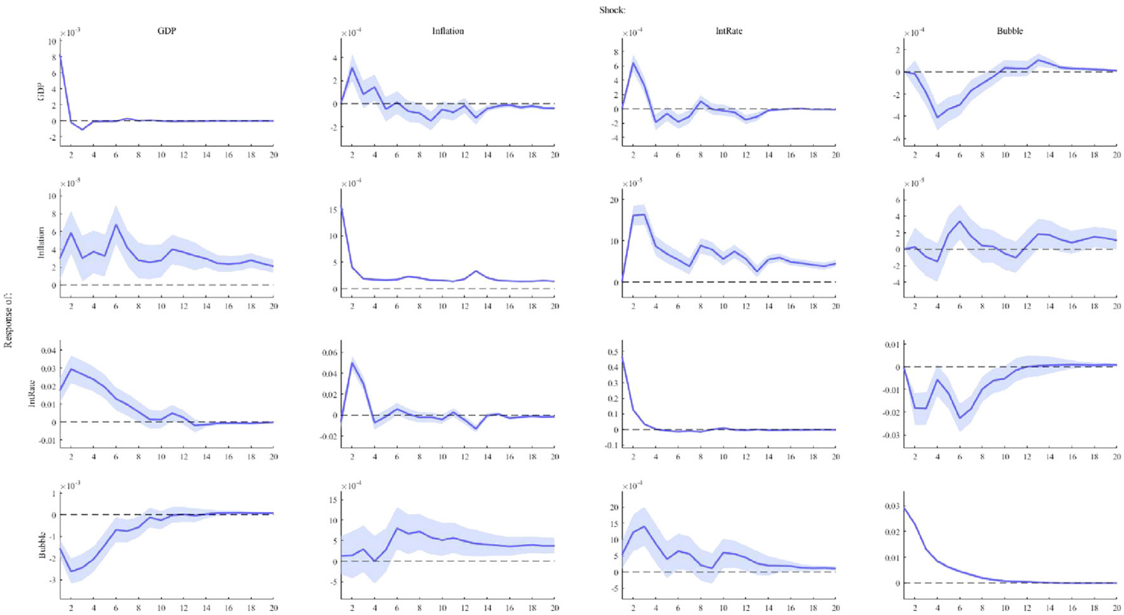


Fig. 2(b). PVAR results with long-term negative bubble.

stock prices are on the decline, the central banks are willing to wait and ensure that such signals are not necessarily idiosyncratic, before deciding to revive the market. All in all, we provide evidence that monetary policy can be used to tackle the formation of bubbles in the equity markets of the G7 countries.

While the focus is on the impact of monetary policy shocks on the bubble indicators, we can also analyze the reverse impact. As is evident from (the 3rd row and 4th column of) Figs. 2(a)–2(f), a positive shock to the positive bubble indicators significantly increases the interest rate, particularly under the short-term indicator, and in a delayed manner for the other two scales, while the opposite holds true when there is a positive shock to the negative bubble indicators, but across all the time-scales with similar magnitudes. Also, for an equal-sized shock to the bubble indicators, monetary policy seems to be reacting more strongly in the absolute sense following an increase in the negative bubble indicator than the positive

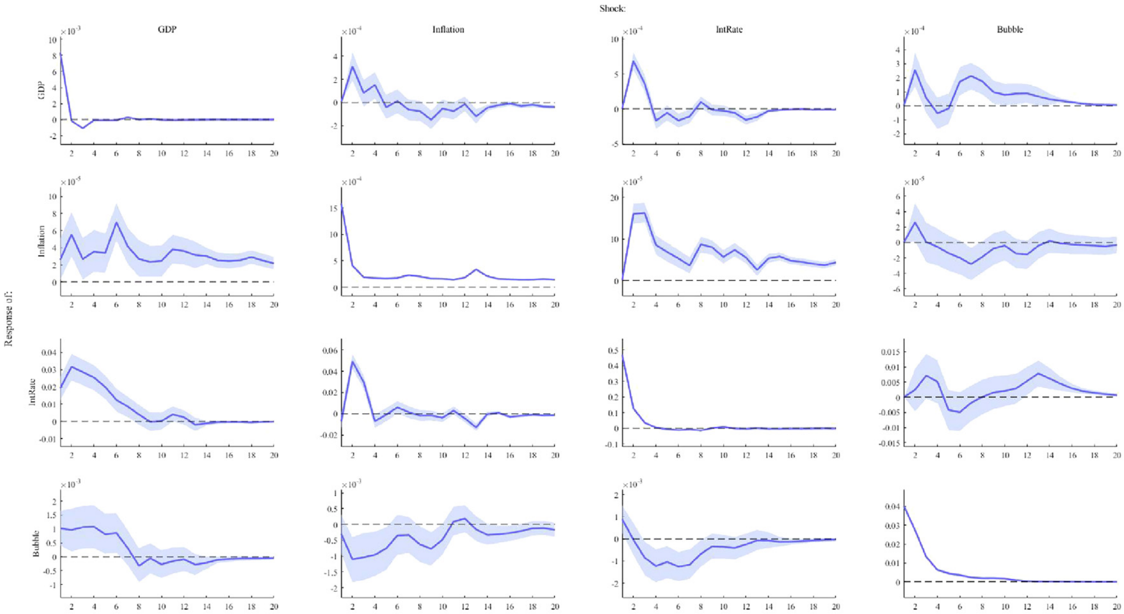


Fig. 2(c). PVAR results with medium-term positive bubble.

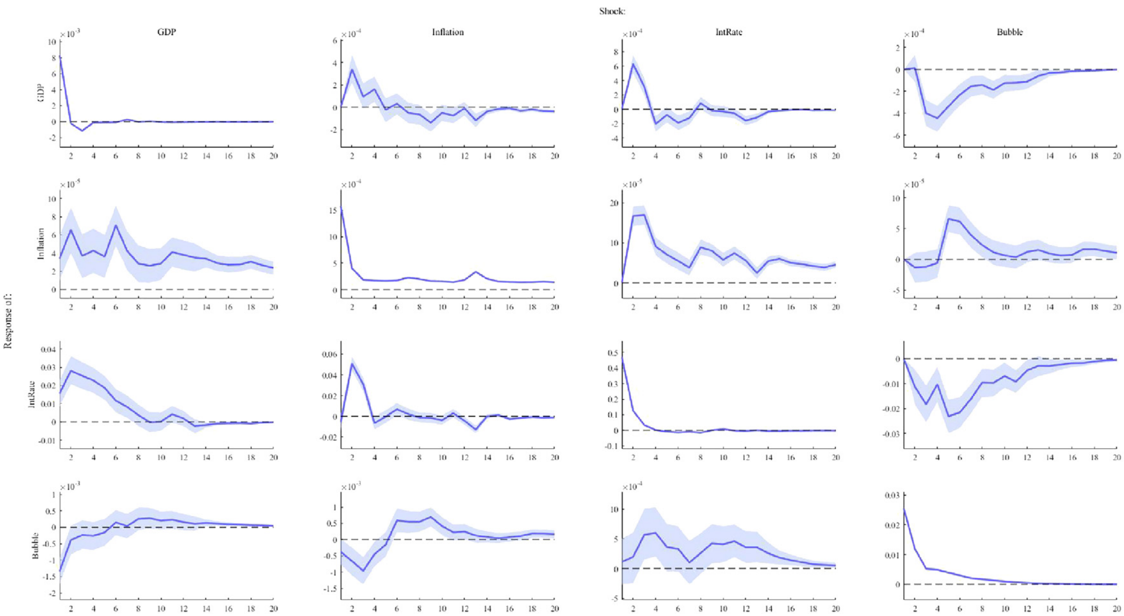


Fig. 2(d). PVAR results with medium-term negative bubble.

one, i.e., monetary authorities are more inclined to revive the stock market, than trying to prevent it from accelerating in an excessive manner.

Based on the suggestion of the editors of the special issue, we conducted a robustness analysis, whereby the monetary policy variable was ordered last now, while output growth, inflation and the specific bubble indicator were placed before it, in line with observations made in the VAR literature involving the real economy-financial market nexus (see for example, Bjørnland and Leitemo (2009), Bjørnland and Jacobsen (2013)). These results have been reported in Figs. B.1(a)–B.1(f) in Appendix B of the paper. As can be seen from the impulse responses, such an alternative ordering does not change the final conclusions drawn above regarding the effects of a monetary policy shock on the macroeconomic variables and the bubble indicators. At the same time, our empirical observations continue to remain the same, when we investigate the

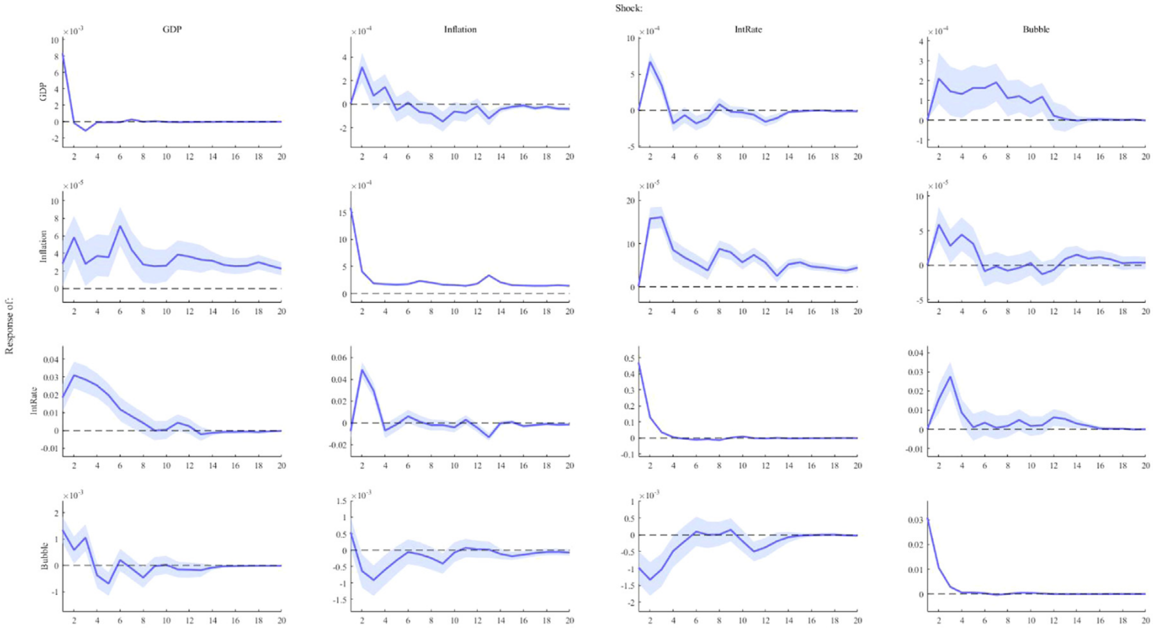


Fig. 2(e). PVAR results with short-term positive bubble.

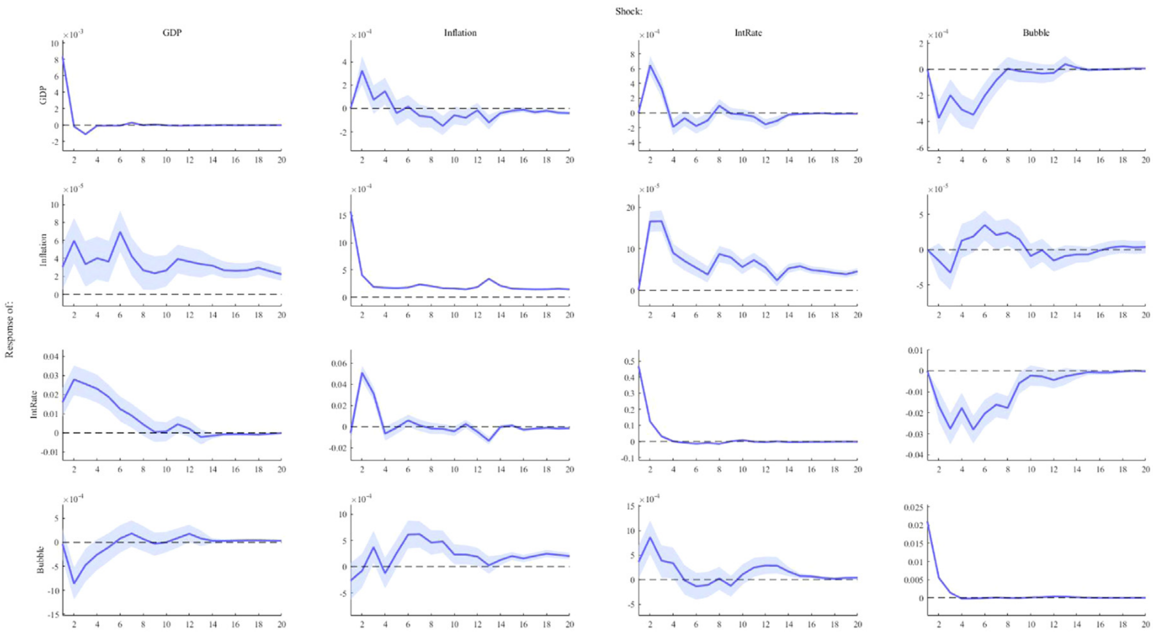


Fig. 2(f). PVAR results with short-term negative bubble.

shock to the bubble indicators. In other words, our findings from the PVAR are robust to alternative orderings of the two key variables of interest namely, monetary policy and the particular equity market bubble indicator under consideration.

In sum, our analysis provides ample evidence that the central banks of the G7 countries can and do indeed ''lean against the wind'' when it comes to the handling of stock market bubbles using conventional and unconventional monetary policy decisions.[8]

[8] In light of the suggestion of an anonymous referee, that we must comment on how our results might change in the wake of the financial turmoil witnessed due to the continuing Russia–Ukraine war, we believe that our results are likely to remain unaffected, as the recent up and downswings

4.3. Implications for sustainable development

From a long-term perspective, it must be noted that there is widespread acceptance of the role of stock markets, as a metric of financial development, in promoting macroeconomic growth and associated sustainable development, i.e., the positive finance-growth nexus (Levine and Zevros, 1998; Beck and Levine, 2004; Levine, 2005; Levine et al., 2016). In our context, evidence in favor of this idea can also be found from the 4th row and 1st column of Figs. 2(a)–2(f), whereby a positive shock to the positive bubbles indicator increases output growth, while the same to a negative bubbles indicator reduces output growth, i.e., bubbles can be growth enhancing (Olivier, 2000).[9] At the same time, from the perspective of monetary decisions, our results imply that the G7 central banks have been closely monitoring the stock markets and designing appropriate interest rate policy in response, to ensure that extreme movements in the market do not adversely impact the growth path and hence, sustainable development in these countries. The issue of sustainability comes to the fore, as stock market movements, including bubbles, not only impact the growth process, but also economic welfare (Futagami and Shibata, 1999; Wang and Wen, 2012; Narayan et al., 2016), and hence have broader consequences for development. Naturally, extreme movements in the equity market need to be controlled to reduce the vulnerability of the population and promote the process of sustainable development in the long-run, especially given the importance of the long-term positive bubble indicators being associated with deep crises.

5. Conclusion

The primary objective of our paper is to analyze the impact of conventional and unconventional monetary policy shocks on equity market bubbles of the G7 countries, and also to investigate whether there is feedback from bubbles to monetary policy decisions.

In this regard, we first detect positive and negative bubbles in the short-, medium- and long-run for the stock markets of these advanced countries by using the LPPLS Multi-Scale Confidence Indicator approach. Our findings revealed major crashes and rallies in the seven stock markets over the monthly period of 1973:02 to 2020:09. Furthermore, we also observed similar timing of strong (positive and negative) LPPLS indicator values across the G7 countries, suggesting commonality in the boom-bust cycles of these stock markets. In other words, diversification of investor portfolios across advanced equity markets is not a possibility for the market agents across investment horizons and during both booms and crashes. However, information on short-term boom-bust cycles can be utilized by investors to predict the deeper extreme movements of the equity markets, associated with the medium- and long-term bubbles, and hence can allow them to make investment decisions on safe-haven assets in their portfolio holdings. In the second step, we developed a panel VAR model to capture the interrelationship between monetary policy and bubbles, while controlling for output growth and inflation, and allowing for various forms of asymmetry that are conveyed by the 6 bubble indicators, in terms of the three time-scales, and also whether the developing bubbles are positive (upward accelerating price followed by a crash) and negative (downward accelerating price followed by a rally). We find statistically significant evidence indicating that monetary policy tends to impact the bubbles in the short- and medium-term the strongest, especially the positive ones. With short- and medium-term bubble indicators shown to lead long-term ones associated with deeper crashes and rallies, our results imply that monetary policy can be used to control G7 stock market bubbles in a timely manner before they are formed. Hence, we provide evidence in favor of "leaning against the wind". Academically, this also implies the violation of the efficient market hypothesis, with booms and busts in stock markets being driven by a monetary fundamental. And with the significant statistical effect of the bubbles on interest rates too, we confirm that monetary authorities in these advanced economies have indeed been responding to the boom-bust cycles, with relatively more intent in recovering the markets than preventing the overheating of the same. Finally, our observation that positive bubbles can be growth enhancing, associates the role of the stock market with the notion of possible sustainable development, given the relationship between bubbles and economic welfare.

As part of future research, it would be interesting to extend our study to emerging stock markets, and also other asset markets (particularly housing, given its well-established role in the GFC Gupta et al., 2023) of both developed and developing economies. In addition, given the importance of behavioral factors, for example, investor sentiment, in driving bubbles (see, Pan, 2020 for further details), it might be worthwhile to extend our analysis by incorporating such predictors in our model.[10] It is likely that, the effect of monetary policy is also going to be contingent on the regimes of such factors

of the equity markets are more due to geopolitical risks and portfolio reallocations, rather than bubbles, i.e., deviations from fundamentals. Besides, extending the sample by about two years or so is likely to have quite marginal average impacts in any case given the already large sample size that we are utilizing over 1973–2020. Also recall, such an extension would also incorporate the period of recovery following the COVID-19 outbreak, with the pandemic again impacting the stock market via fundamentals, rather than through bubbles — a conclusion we can draw based on the small-sizes of the LPPLS-CIs over the majority part (nine months) of the year of 2020 included in our sample.

[9] In comparison, the effect on inflation is not necessarily significant but does seem to align with the fact that bubble shocks can be considered to be demand shocks, with positive bubbles increasing inflation, and negative ones reducing the same.

[10] As a preliminary analysis, we used the nonparametric causality-in-quantiles test of Jeong et al. (2012), which captures the predictability of the entire conditional distribution of the dependent variable, i.e., it states, to capture the causal impact of a metric of global sentiment (natural logarithmic values of the gold-to-platinum price ratio Huang and Kilic, 2019) on the six bubble factors derived from the DFMs (discussed in Footnote 5). Note the gold and platinum prices in US dollars were derived from: https://www.kitco.com/. As can be seen from Fig. C.2 in Appendix C, this metric of global sentiment does carry strong predictive information over the entire conditional distribution of each of the six bubbles factors, i.e., predictability holds at each point in time corresponding to various states of the indicators – a finding which was also confirmed by the time-varying test of causality of Rossi and Wang (2019), which is available upon request from the authors.

(Çepni and Gupta, 2021; Çepni et al., 2021). Finally, while we do identify bubbles in a time-varying fashion, and also consider both conventional and unconventional monetary policy decisions, a limitation of our study is that we rely on a constant parameter PVAR, which can be extended in the future to a time-varying set-up (Koop and Korobilis, 2019). The time-varying PVAR can also be utilized for forecasting the bubble indicators in real-time, based on the information content of conventional and unconventional monetary policies, besides output growth and inflation.

Acknowledgments

We would like to thank three anonymous referees and the guest editors of the special issue, Professor Chien-Chiang Lee and Professor Chi-Chuan Lee for many helpful comments. However, any remaining errors are solely ours.

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Appendix A. A theoretical framework of bubbles and monetary policy

Using the partial equilibrium asset pricing model of Galí and Gambetti (2015), which is devised for an economy populated by risk-neutral investors, where R_t stands for the riskfree real interest rate, P_t denotes prices at time t and D_t represents the dividend stream, as our foundation. We treat the prices at any moment as a sum between a "fundamental" component (P_t^F) and a "bubble" component (P_t^B), as shown in the following equation:

$$P_t = P_t^F + P_t^B \tag{A.1}$$

We next consider that P_T^F is given by the present discounted value of future dividends, as reflected by Eq. (A.2). This in turn can be expressed in log-linear form as in Eq. (A.3).

$$P_t^F = E_t\{\sum_{k=1}^{\infty}(\prod_{j=0}^{k-1}\frac{1}{R_{t+j}})D_{t+k}\} \tag{A.2}$$

$$p_t^F = c + \sum_{k=0}^{\infty}\lambda^k[(1-\lambda)E_t\{d_{t+k+1}\} - E_t\{r_{t+k}\}] \tag{A.3}$$

In the above context, c is a constant and $\lambda = \frac{\Gamma}{R}$, with Γ the growth rate for dividends and R the same for the interest rate. In this setup, we assume that the responses of these two components to an exogenous shock ϵ_t^m will yield the impact of interest rate shocks on asset prices and bubbles. Therefore, taking the first derivative of Eq. (A.3) with respect to the exogenous shock and obtain:

$$\frac{\partial p_{t+k}}{\partial \epsilon_t^m} = (1-\gamma_{t-1})\frac{\partial p_{t+k}^F}{\partial \epsilon_t^m} + \gamma_{t-1}\frac{\partial p_{t+k}^B}{\partial \epsilon_t^m}, \tag{A.4}$$

where $\gamma_t = P_t^B/P_t$ and shows the fraction of the bubble component for a certain price, at time t. We can now assert that the response of p_t^F, using this specification and Eq. (A.2), can be expressed as:

$$\frac{\partial p_{t+k}^F}{\partial \epsilon_t^m} = \sum_{j=0}^{\infty}\lambda^j((1-\lambda)\frac{\partial d_{t+k+j+1}}{\partial \epsilon_t^m} + \frac{\partial r_{t+k+j}}{\partial \epsilon_t^m}) \tag{A.5}$$

Both standard economic reasoning and the empirical literature consider that a rise in the real interest rate would result in a contraction in the fundamental component (such that $\frac{\partial p_{t+k}^F}{\partial \epsilon_t^m} \leq 0$), but that it is also expected in the bubble component (i.e., $\frac{\partial p_{t+k}^B}{\partial \epsilon_t^m} \leq 0$), as noted by Galí and Gambetti (2015). As a result, the aggregate impact on a certain asset price should also be negative:

$$\frac{\partial p_{t+k}}{\partial \epsilon_t^m} \leq 0 \tag{A.6}$$

However, Galí and Gambetti (2015) revisit the arguments found in Galí (2014) and point out the fact that the hypothesis of a negative reaction of a bubble to interest rate expansions lacks theoretical support and goes against normal intuition. We assume, to examine this theoretically, that Eq. (A.7) holds in a rational expectations equilibrium, and that the expression of the fundamental component, as given in Eq. (A.2) satisfies Eq. (A.8).

$$P_t R_t = E_t\{D_{t+1} + P_{t+1}\} \tag{A.7}$$

$$P_t^F R_t = E_t\{D_{t+1} + P_{t+1}^F\} \tag{A.8}$$

If we now consider Eq. (A.1) in conjunction with the last two equations, we can confirm that the bubble component satisfies the following expression:

$$P_t^B R_t = E_t\{P_{t+1}^B\} \tag{A.9}$$

In log-linear form, Eq. (A.9) becomes:

$$E\{\Delta p_{t+1}^{b}\} = r_t \tag{A.10}$$

As such, the bubble component has a positive reaction to a hike in the interest rate, which goes against mainstream considerations on the linkages between interest rates and bubbles. There is then also the comovement channel through which interest rates can influence bubbles (Galí and Gambetti, 2015). Therefore, let us now consider the above expression at $t-1$ while discarding the expectation operator.

$$\Delta p_t^{b} = r_{t-1} + \xi_t \tag{A.11}$$

In Eq. (A.11), $\xi_t = p_t^B - E_{t-1}p_t^B$ is an arbitrary process that satisfies the martingale-difference feature, while it is also not necessarily connected to fundamentals or interest rate dynamics (Galí and Gambetti, 2015), and therefore:

$$\xi_t = \psi_t(r_t - E_{t-1}[(r_t)]) + \xi_t^{*} \tag{A.12}$$

In the above set-up, ψ_t is a random parameter without theoretical restrictions in terms of the sign, size, or dependence on policy regime. Hence, the reaction of the bubble component to monetary shocks is formulated as:

$$\frac{\partial p_{t+k}^{B}}{\partial \epsilon_t^{m}} = \begin{cases} \psi_t \frac{\partial r_t}{\partial \epsilon_t^{m}}, & \text{for } k = 0 \\ \psi_t \frac{\partial r_t}{\partial \epsilon_t^{m}} + \sum_{j=0}^{k-1} \frac{\partial r_{t+j}}{\partial \epsilon_t^{m}}, & \text{for } k = 1, 2, \ldots \end{cases} \tag{A.13}$$

Although the initial reaction given by ψ_t is indeterminate, the long-run influence of monetary policy shocks on bubble magnitude will be either positive or negative, in case the dimension of the real interest rate response is large enough to offset any initial impact (Galí and Gambetti, 2015).

Appendix B. PVAR with alternative ordering

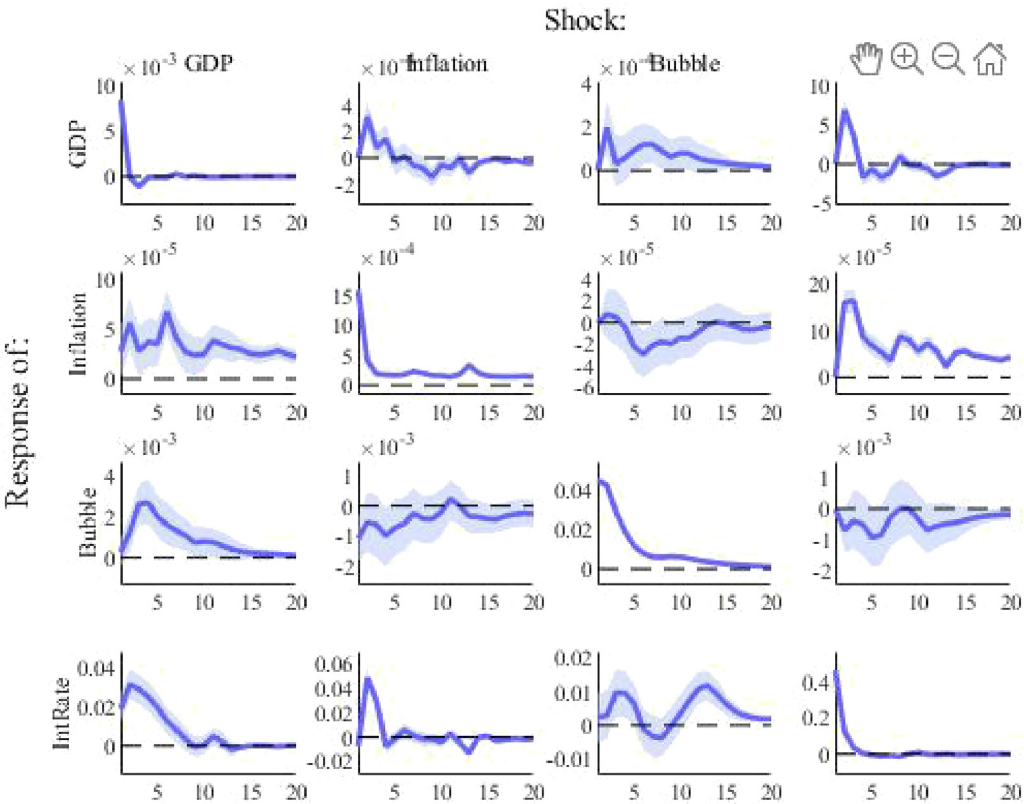

Fig. B.1(a). PVAR results with long-term positive bubble.

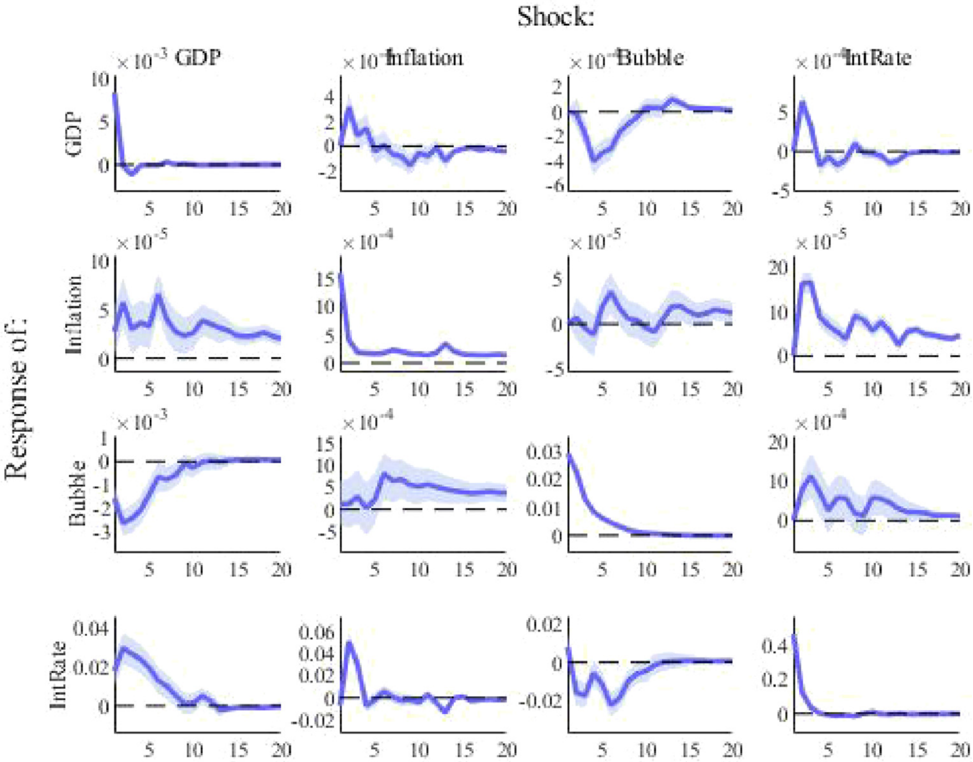

Fig. B.1(b). PVAR results with long-term negative bubble.

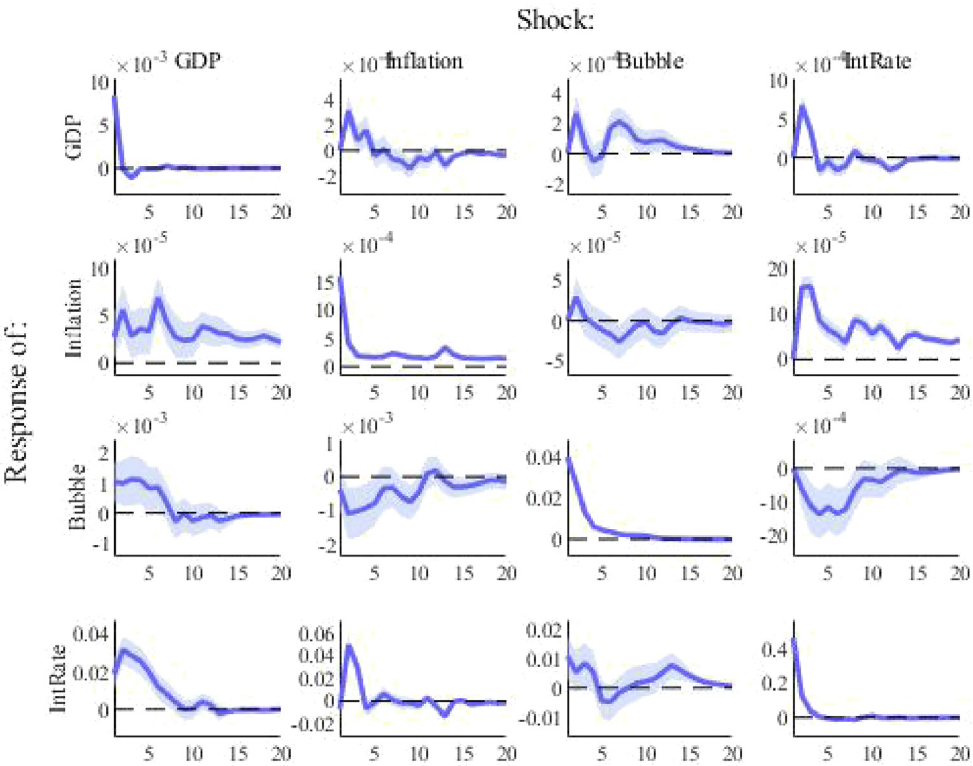

Fig. B.1(c). PVAR results with medium-term positive bubble.

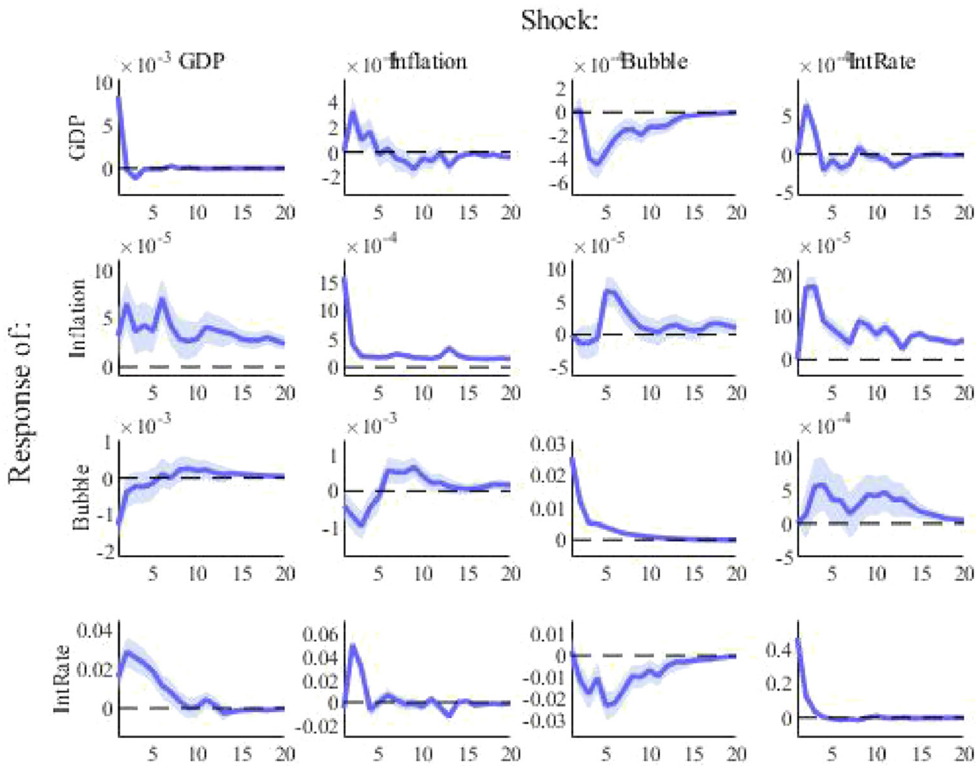

Fig. B.1(d). PVAR results with medium-term negative bubble.

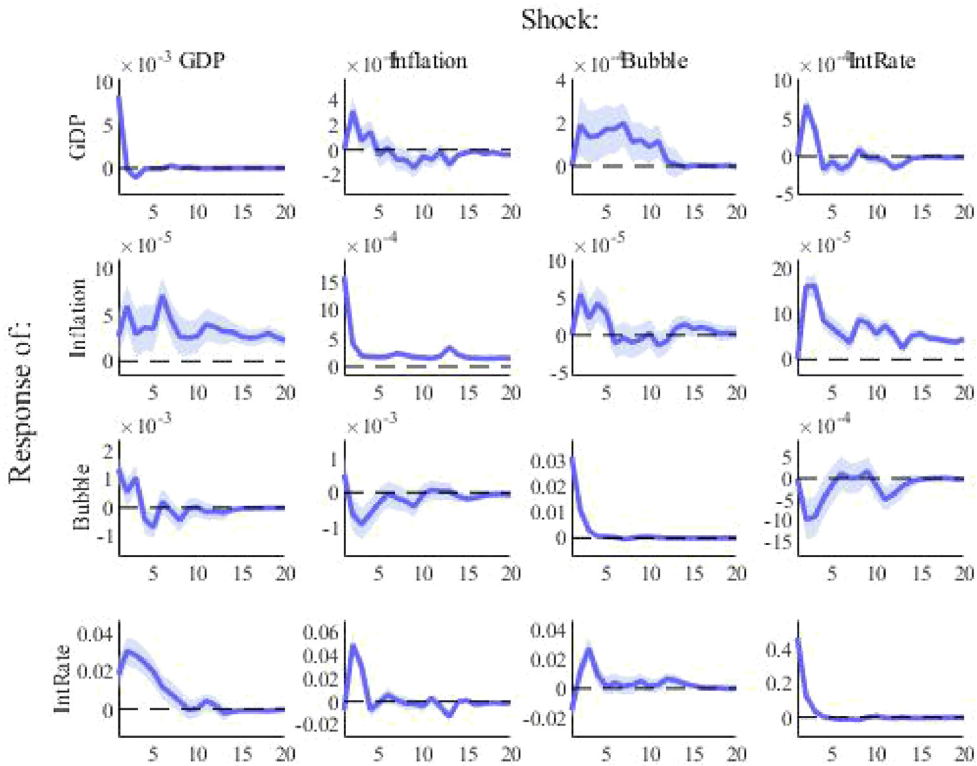

Fig. B.1(e). PVAR results with short-term positive bubble.

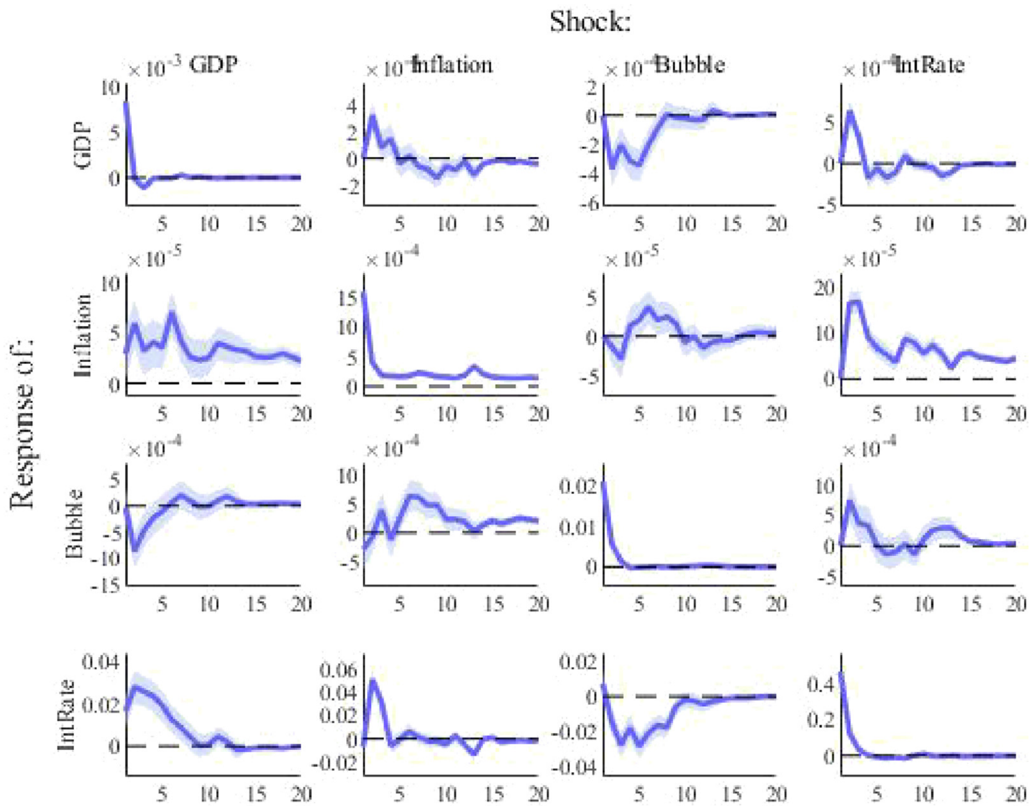

Fig. B.1(f). PVAR results with short-term negative bubble.

Appendix C

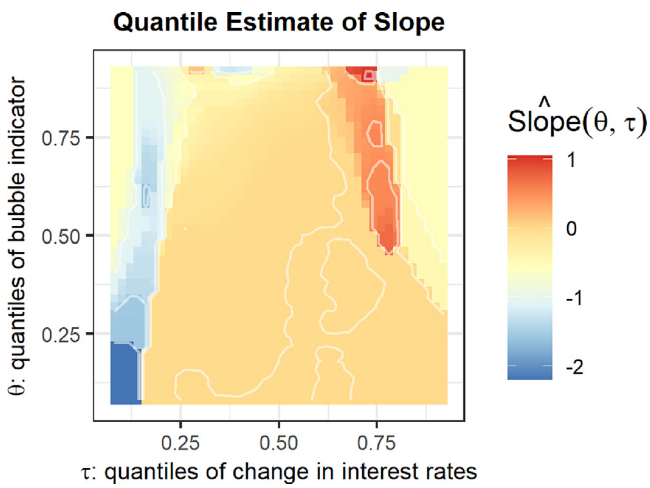

Fig. C.1(a). Impact on long-term positive bubbles indicator.

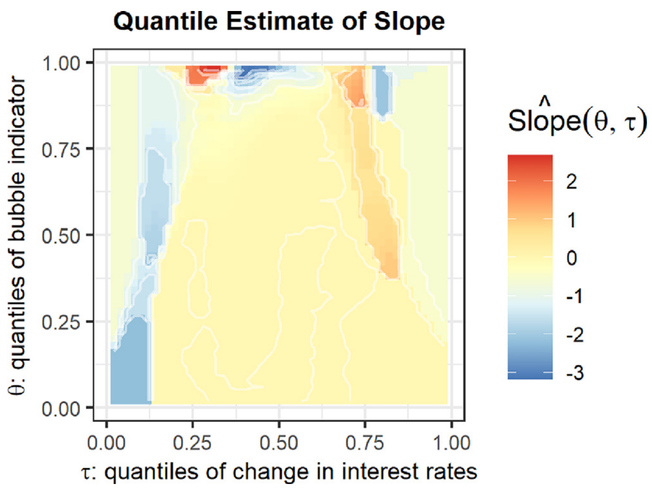

Fig. C.1(b). Impact on long-term negative bubbles indicator.

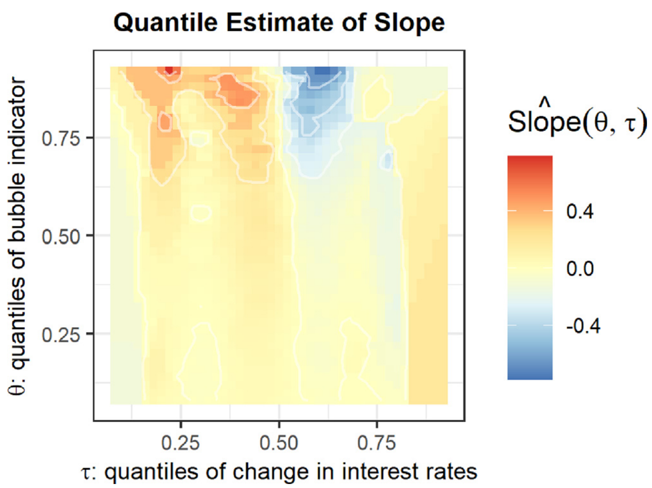

Fig. C.1(c). Impact on medium-term positive bubbles indicator.

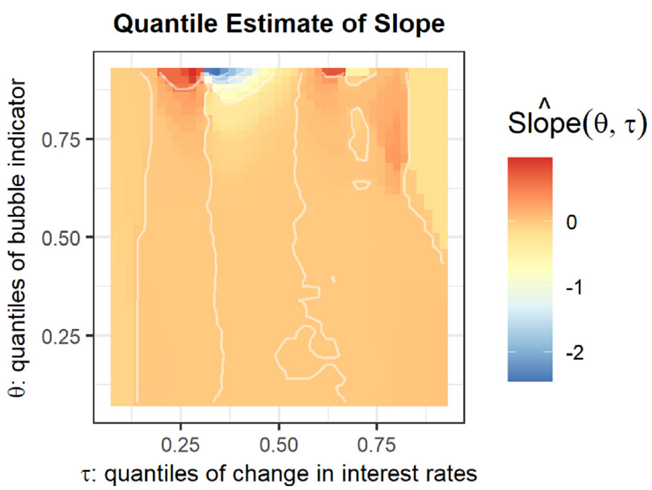

Fig. C.1(d). Impact on medium-term negative bubbles indicator.

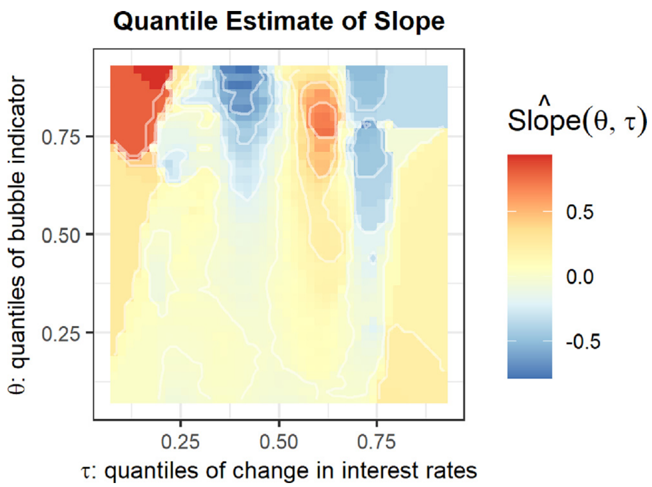

Fig. C.1(e). Impact on short-term positive bubbles indicator.

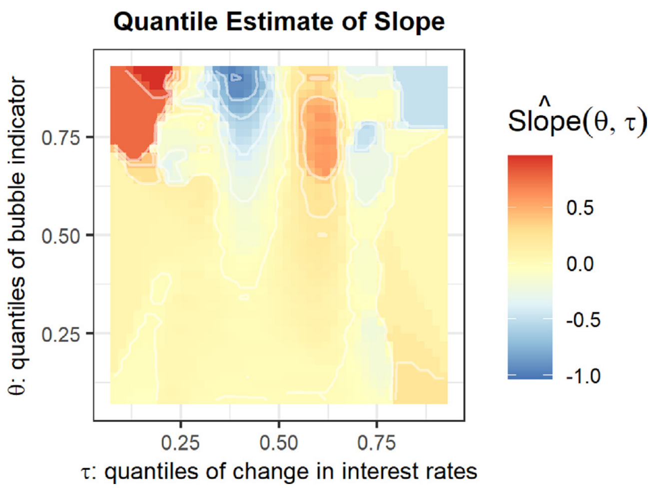

Fig. C.1(f). Impact on short-term negative bubbles indicator.

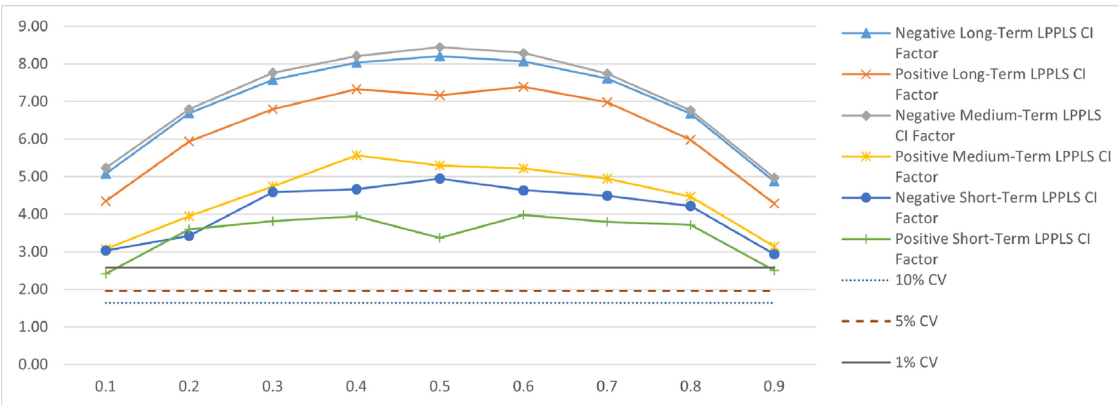

Fig. C.2. Causality-in-quantiles test of the effect of gold-to-platinum ratio on the bubbles factors.
Note: Vertical axis presents the values of the standard normal test statistics corresponding to the null that the log of gold-to-platinum price ratio (global metric of sentiment) does not Granger cause the specific multi-scale LPPS CI factor; Horizontal axis measures the quantiles; 10%, 5% and 1% percent critical values of 1.645, 1.96, and 2.575 respectively.

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