Gold, platinum and the predictability of bubbles in global stock markets

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Abstract

This paper examines the predictability of bubbles across global stock markets and whether or not synchronicity in bubble formation across markets can be predicted via metrics of market risk that are readily available. Utilizing the gold to platinum price ratio (LGP) as an easy to implement risk metric and the Log-Periodic Power Law Singularity (LPPLS) model to detect positive and negative bubble formation at different time scales, we document evidence of synchronized boom and bust cycles of the seven developed equity markets in the G7 bloc. More importantly, our analysis shows that bubbles and their comovements are predictable by the gold to platinum price ratio although the predictive relationship is only detectible via models that account for non-linearities in the data. We find that predictability is generally stronger for negative bubbles than their positive counterparts and the predictive impact of LGP is strongest for the long-term for negative bubbles, while it is strongest in the short-run for positive bubbles, meaning that the gold to platinum price ratio serves as a more robust predictor of deeper downward accelerating price formations followed by a rally. The predictability results for the U.S. also carries over to bubble formation in the remaining stock markets of the G7 bloc, to the extent that the gold to platinum price ratio also helps to explain the synchronicity of bubbles across the G7. Our findings provide a valuable opening for market regulators as the results show that readily available metrics of market risk can be used to model and monitor the occurrence of bubbles in financial markets as well as the connectedness of bubbles across the global markets.

JEL Classification: C22, G15, Q02
Keywords: Multi-Scale Positive and Negative Bubbles; Gold-to-Platinum Price-Ratio; Nonparametric Causality-in-Quantiles Test; G7

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1. Introduction

Price bubbles in financial markets reflect deviations from fundamental values which can occur within a rational, efficient market setting or as a result of inefficiencies in market mechanisms that eventually pave the way to bubble formations and subsequent crashes in asset prices. While modelling rational expectation bubbles is often plagued with join hypothesis issues, a large number of works argue that bubbles occur due to market inefficiencies associated with heterogeneous beliefs (Scheinkman and Xiong, 2003), information asymmetries (Allen and Gorton, 1993), information cascades by noise traders (De Long et al., 1990; Shleifer, 2000) as well as limits to arbitrage (Shleifer and Vishny, 1997; Abreu and Brunnermeier, 2003; among others). Despite the multitude of studies that focus on the detection of price bubbles in different contexts, however, the predictability of bubbles is relatively understudied. Furthermore, the literature has not provided any insight to the connectedness of bubbles across global financial markets although the issue has significant implications for the stability of the financial system and policy making.

This paper provides novel insight to the literature on bubbles in financial markets by examining the predictability of bubbles across a wide range of global stock markets and whether or not synchronicity in bubble formation across markets can be predicted via metrics of market risk that are readily available. This is an important consideration for not only pricing and risk management purposes, but also for policy making as market regulators can use the results from such a predictive analysis to improve the accuracy of forecasting models for boom and bust market conditions and their spillover effects across markets. Furthermore, it is now theoretically (Biswas et al., 2020) and empirically (Reinhart and Rogoff, 2009; Brunnermeier and Oehmke, 2013; Jordà et al., 2015) established that bursting of bubbles leads to protracted recessions and substantial economic losses. Understandably then, a high-frequency analysis of bubble detection and its predictability across markets is of paramount importance to policymakers for the design of appropriate policy responses as boom-bust cycles in stock markets are likely to be informative about the future path of low frequency macroeconomic variables, with the information being fed into mixed data sampling (MIDAS) models for nowcasting (Bańbura et al., 2011) in addition to its welfare implications (Narayan et al., 2016).

In our application, we employ the popularly utilized Log-Periodic Power Law Singularity (LPPLS) model of Johansen et al. (1999, 2000) and Sornette (2003) to detect positive (upward accelerating price followed by a crash) and negative (downward accelerating price followed by a rally) bubbles and apply them to a large number of global stock markets including those in the G7 bloc. Arguing that a bubble can emerge intrinsically out of the natural functioning of the market, the LPPLS model aims to detect super-exponential growth of asset prices by modeling deviations around the price growth in a market setting that is governed by sentiment rather than some real underlying value (Sornette and Cauwels, 2015). In this setting, while agents are fully aware of the mispricing, the price continues to rise due to a lack of synchronization of the arbitragers, either due to disagreements about the time of the beginning (Abreu and Brunnermeier 2003) or of the end (Demos and Sornette, 2017) of the bubble. Next, following Demirer et al. (2019), we compute the multi-scale LPPLS confidence indicators to characterize positive and negative bubbles at the short, medium, and long-time scales. Unlike other bubble detection methodologies (see Balcilar et al., 2016; Zhang et al., 2016; and Sornette et al., 2018 for detailed reviews), our model allows us to identify both positive and negative multi-scale bubbles, paving the way for our subsequent predictive analysis to assess the possible asymmetric predictive effects of market uncertainty over bubble formation at different time scales. This is an important consideration in terms of the practical applications of bubble prediction as crashes and recoveries at different time horizons can convey different information for market participants, in line with the Heterogeneous Market Hypothesis (HMH; Müller et al., 1997).[1]

Having identified positive and negative bubbles at different time scales, our subsequent analysis focuses on the predictability of these bubbles via risk metrics that are readily available for market participants. To that end, we employ the gold to platinum price ratio (*GP*) of Huang and Kilic (2019) as an easy to implement risk metric that is shown to capture persistent variation in risk and predict future stock returns in the time series. Considering the dual nature of gold as both a consumption good (mostly jewellery) and an investment tool that preserves value during times of distress, while platinum is a precious metal with similar uses as gold in consumption, Huang and Kilic (2019) argue that the ratio of gold to platinum prices should be largely insulated from shocks to consumption and jewellery demand, thus capturing information on the variation in aggregate market risk. This risk metric has been shown to serve as a robust predictor of equity returns in the United States (US) and other developed stock

[1] 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.

markets, both at the aggregate- and cross-sectional levels, as well as for industry returns (Pham and Rudolf, 2021), bond risk premia (Bouri et al., 2021) and tail risks (Salisu et al., 2022).[2]

As noted by Lehnert (2020), periods of fear and euphoria can be associated with high and low aversion towards risk, respectively, translating into weak (strong) investor sentiment as captured by the corresponding high and low values of *GP*. In that regard, the literature provides several channels by which investor sentiment and bubble formation in financial markets can be related (see, Scherbina and Schlusche (2014) for a detailed review). The first class of models concerns the differences of opinion and short sale constraints, arguing that in a market where optimistic investors are boundedly rational, or simply dogmatic about their beliefs, they fail to consider that other agents in the economy may have more pessimistic views about an asset, but cannot sell it due to short sale constraints. In this scenario, the resulting market price of the asset remains too high relative to the fair value. In contrast, the second class of models incorporate feedback trading which paves the way to bubble formation as one group of traders builds their trading demands solely on past price movements, hence driving bubble formation for a period of time before the bubble eventually collapses. The third theoretical model is based on a biased self-attribution model wherein a representative investor suffers from biased self-attribution, which leads other agents to consider signals that confirm their beliefs and dismiss noise signals that contradict their beliefs. Finally, the fourth model builds on the representativeness heuristic, which combines two behavioural phenomena, the representativeness heuristic and conservatism bias. The representativeness heuristic leads investors to put too much weight on attention-grabbing (strong) news, which leads to overreaction; whereas, conservatism bias is the investors' tendency to be too slow to revise models such that they under-weigh relevant but non-attention-grabbing (routine) evidence, which in turn leads to under-reaction. Against this theoretical background, our analysis extends the literature on sentiment and bubble formation in a novel direction regarding the predictability of stock market bubbles via proxies of market sentiment or risk.

The predictive analysis is conducted via the nonparametric causality-in-quantiles test proposed by Jeong et al. (2012). Our employed test is a more elaborate procedure for detecting causality at each point of the bubble indicators, capturing the existence or non-existence of

[2] Huang and Kilic (2019) develop a theoretical model where *GP* is insulated from shocks to consumption, since they affect gold and platinum prices equally, in which increases in disaster probabilities raise risk premiums, leading to higher discount rates and lower stock prices. While gold and platinum prices fall due to higher discount rates, gold prices fall by less than platinum prices due to the higher countercyclical component of its service flow. As a result, *GP* is shown to be high when stock prices are low and the equity risk premium is high, thus providing the ratio with the power to predict future stock returns.

predictability due to *GP* at various quantiles of the bubble confidence indicators, which makes the predictive analysis inherently time-varying in nature. As a more general test, our method is more likely to identify causality at specific quantiles when the conditional mean-based tests may fail. Additionally, since we do not need to determine the number of regimes as in Markov-switching models of causality (Ben Nasr et al. 2015; Balcilar et al. 2018a) and can test for predictability at each point of the conditional distribution characterizing specific bubble regimes, our method does not suffer from any misspecification in terms of specifying and testing for the optimal number of regimes. To the best of our knowledge, ours is the first study to analyse the high-frequency predictive impact of gold to platinum rice ratio on multi-scale positive and negative bubbles using a nonparametric quantiles-in-causality approach.

Our findings show that the LPPLS framework is a flexible tool for detecting positive and negative bubbles across different time scales. We find that shorter time scale indicators are best suited for detecting smaller crashes or rallies, while the medium and longer time scale indicators are best suited for detecting larger crashes or rallies. While the long-term scale confidence indicators produce fewer signals, they appear to capture larger crashes or rallies, and the shorter scale indicators generate more frequent signals that precede smaller crashes or rallies. Furthermore, we observe significant evidence of synchronized boom and bust cycles of the seven developed equity markets in the G7 bloc, implied by positive contemporaneous correlations for both the positive and negative bubble indicators based on a Bayesian Gaussian graphical vector autoregressive framework. More importantly, our analysis shows that bubbles and their comovements are predictable by the gold to platinum price ratio although the predictive relationship is only detectible via models that account for non-linearities in the data. While predictability is generally stronger for negative bubbles than their positive counterparts, we find that the predictive impact is strongest for the long-term, followed by the medium- and short-term indicators for negative bubbles. In the case of the positive bubbles, causality is found to be strongest in the short-run, meaning that the gold to platinum price ratio serves as a more robust predictor of deeper downward accelerating price formations followed by a rally, i.e., long- and medium-term negative bubbles. Our findings provide a valuable opening for market regulators as the results show that the readily available metric of market risk based on the gold to platinum price ratio can be used to model and monitor the occurrence of bubble patterns in financial markets as well as the connectedness of these bubbles across the global markets.

The remainder of the paper is organized as follows. Section 2 outlines the methodologies associated with the detection of bubbles and the predictive analysis along with the data used in the empirical analysis. Section 3 presents the empirical results and Section 4 concludes the paper.

2. Methodology & Data

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

The first part of our analysis focuses on quantifying the multiscale positive and negative bubble indicators. To this end, we use the stable and robust Log-Periodic Power Law Singularity (LPPLS) model calibration scheme developed by Filimonov and Sornette (2013).[3] This framework builds on a setting in which herding behavior of noise traders destabilizes asset prices via correlated trades and the risk of a crash from herding behavior is modeled as a sum of power law singularity associated with large scale amplitude oscillations that are periodic in the logarithm of the time to singularity of critical time. In this framework, the expected trajectory of the log price is modeled via

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

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

As noted by Demirer et al. (2019), the power law singularity captures the positive feedback mechanism associated with the correlated trades driven by herding behaviour of noise traders. In this framework, the log-periodic oscillations represent the tension and competition between the traders who act upon rational expectations and noise traders who tend to engage in herding behavior, thus resulting in deviations around the faster than-exponential price growth as the market approaches a finite-time-singularity at t_c. Following Filimonov and Sornette (2013), Equation (1) is reformulated to reduce the complexity of the calibration process by eliminating the nonlinear parameter ϕ and expanding the linear parameter C to be $C_1 = C\ \cos\phi$ and $C_2 = C\ \cos\phi$. The new formulation yields

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

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

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 three nonlinear parameters, i.e. $\{t_c, m, \omega\}$, and four linear parameters, i.e. $\{A, B, C_1, C_2\}$, 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 as

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

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

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

where the hat symbol indicates the estimated parameters. The four linear parameters are estimated by solving the optimization problem:

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

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

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

Finally, the three nonlinear parameters are determined by solving the following nonlinear optimization problem:

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

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

In our empirical analysis, we explore the predictability of negative and positive bubble patterns as well as their predictability across different time scales. To that end, the LPPLS confidence indicator, introduced by Sornette et al. (2015), provides an appropriate setting to capture asymmetric bubble dynamics across the short and long horizons. In this framework, positive bubbles are captured within a scenario wherein the price of an asset grows super-exponentially towards t_c, eventually resulting in a change of regime (in general a crash). Similarly, negative bubbles are captured as the exact mirror of positive bubbles with respect to the horizontal axis, featured by an accelerating price drop, resulting in a regime change that is generally in the form of a substantial price appreciation, i.e. a potential 'negative' crash. The LPPLS confidence indicators (CI) are estimated using the log price-dividend ratio time series of each asset (each stock market index in our case) such that the larger the confidence indicator value, the more reliable the LPPLS bubble pattern and vice versa. The indicator series is computed 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 Demirer et al. (2019), we incorporate bubbles of varying multiple time-scales into our analysis and sample the time series in steps of 5 trading days. We create the nested windows $[t_1, t_2]$ and iterate through each window in steps of 2 trading days. In this way, we obtain a weekly resolution, based on which we construct the following indicators:

- *Short-term bubble:* A number $\in [0,1]$ which denotes the fraction of qualified fits for estimation windows of length $dt := t_2 - t_1 \in [30:90]$ trading days per t_2. This indicator is comprised of $(90 - 30)/2 = 30$ fits.

- *Medium-term bubble:* A number $\in [0,1]$ which denotes the fraction of qualified fits for estimation windows of length $dt := t_2 - t_1 \in [30:90]$ trading days per t_2. This indicator is comprised of $(300 - 90)/2 = 105$ fits.

- *Long-term bubble:* A number ∈ [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.

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

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

The confidence indicators across the short, medium and long-time scales capture the strength of the LPPLS bubble structure in their respective time scales. For example, if the short-term CI takes on a large value, while the medium and long-term CI values are small, this would be an indication of bubble formation recently within the last three months. In our application, this provides an appropriate setting to examine the short and long-term predictability patterns in bubbles using the corresponding confidence indicators at different time scales.

2.2. Nonparametric Causality-in-Quantiles Test

In order to explore the predictive power of the gold-to-platinum price ratio (*LGP*), serving as a metric of risk, over bubble formation in financial markets, we utilize a dynamic methodology that allows us to capture the causal linkages between the gold-to-platinum price ratio and the bubble confidence indicators during various market states. To that end, we utilize the nonparametric quantiles-based causality test developed by Jeong et al. (2012).[4] This test allows us to detect predictability across the entire conditional distributions of the LPPLS-CIs, resulting from the gold-to-platinum price ratio, while simultaneously controlling for misspecification due to uncaptured nonlinearity and structural breaks in these relationships. Accordingly, this econometric framework allows us to circumvent potential misspecification due to nonlinearity and instability, compared to conditional mean-reliant nonlinear and/or nonparametric causality tests (see, for example, Hiemstra and Jones (1994), Diks and Panchenko (2005, 2006), Nishiyama et al. (2011)).

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

Let y_t denote a the LLPLS-CI series for a given stock market and x_t the gold to platinum price ratio, i.e., LGP. Further, let $Y_{t-1} \equiv (y_{t-1}, \dots, y_{t-p})$, $X_{t-1} \equiv (x_{t-1}, \dots, x_{t-p})$, $Z_t = (X_t, Y_t)$, and $F_{y_t|\cdot}(y_t| \bullet)$ denote the conditional distribution of y_t given $\bullet$. Defining $Q_\theta(Z_{t-1}) \equiv Q_\theta(y_t|Z_{t-1})$ and $Q_\theta(Y_{t-1}) \equiv Q_\theta(y_t|Y_{t-1})$, we have $F_{y_t|Z_{t-1}}\{Q_\theta(Z_{t-1})|Z_{t-1}\} = \theta$ with probability one. The (non)causality in the θ-th quantile hypotheses to be tested are:

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

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

such that the rejection of the null implies that x_t causes y_t in the θ-th quantile with respect to the lag-vector of $(y_{t-1}, \dots, y_{t-p}, x_{t-1}, \dots, x_{t-p})$. Jeong et al. (2012) show that the feasible kernel-based test statistics has the following format:

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

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

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

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

2.3. Data

Our dataset includes daily stock price index and dividend series for the US and the remaining six of the G7 countries, in their local currencies, obtained from Refinitiv Datastream. Although our focus is specifically on the US stock market, we also consider the predictive impact of *GP* on bubble formation in international stock markets, namely the entire G7 bloc, as the gold to platinum price ratio can be considered as a metric of risk worldwide considering that gold and platinum are two globally traded commodities. In this regard, the choice of G7 countries was driven by two factors: First, due to the availability reliable stock market data that would allow us to track the behaviour of important episodes of bubbles, and its predictability due to *GP*, spanning nearly half a century, and; second because this group of countries accounts for nearly two-thirds of global net wealth and nearly half of world output, and hence, boom-bust cycles in these stock markets are likely to have a worldwide spillover effect, impacting the sustainability of the global financial system (Das et al., 2019). The natural logarithmic values of the daily price-dividend ratios for each stock market are used to obtain the positive and negative weekly bubble indicators at the short-, medium-, and long- time scales. In line with the existing literature on bubble estimation, we use the price-dividend ratio to model the price trajectory of prices which yields confidence indicator series that are free from the possible effect of currency units and exchange rate movements. Each of the six derived multi-scale LPPLS-CI values for the US, and Canada, France, Germany, Italy, Japan and the UK, is sampled at a weekly frequency. Similarly, the daily gold and platinum price data, in US dollars, is obtained from the London Bullion Market Association (now known simply as LBMA).[5]The daily data is then converted to weekly frequency by taking averages over the number of trading days during a week. We then compute the natural logarithmic values of the unit-free price-ratio of gold-to-platinum prices (*LGP*). The LGP is then matched with the data for the bubble indicators, resulting in 2489 observations over the sample period covering the 1st week of (7th) January 1973 to 2nd week of (13th) September 2020.

Figure 1 presents the natural logarithm of the ratio of gold to platinum prices (LGP) on a weekly frequency. While the data exhibits a rather stable pattern for much of the early part of the 2000s, we observe a clear regime change into a persistent rising pattern with the global financial crisis in 2007, indicating the increased risk in financial markets that has not really subsided since the global financial crisis. Table 1 presents several summary statistics for the U.S. stock market. Clearly, the bubble indicator series exhibit non-normal behaviour with the presence of extreme values in both directions along positive skewness. At the same, we observe higher mean values for positive bubble indicator series across all time scales, implying the prevalence of booms in stock market dynamics as opposed to crash patterns. Overall, our preliminary checks indicate that the MS-LPPLS confidence indicators successfully capture the

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[5] https://www.lbma.org.uk/prices-and-data/precious-metal-prices#/.

bubble-like patterns in global financial markets, while the descriptive statistics provide the initial motivation for our quantiles-based causality framework.[6]

[INSERT FIGURE 1]

[INSERT TABLE 1]

3. Empirical Findings

3.1. Bubble Detection

Figure 1 presents the time series plots for the Multi-Scale Log-Periodic Power Law Singularity Confidence Indicators (MS-LPPLS-CIs) of the G7 countries. The CI series at each time scale is shown in different colours with the short, medium and long-term indicators displayed in green, purple and red color, respectively, while the log price-to-dividend ratio is displayed in black. Higher confidence indicator values for a particular scale indicate that the LPPLS signature is present for many of the fitting windows to which the model was calibrated, making it more reliable. From a brief visual inspection of the plots in Figure 1, we find that there are many spikes in the bubble indicator values preceding regime shifts in the underlying log price-to-dividend ratio.

The long-term positive LPPLS-CI (red lines in Figure 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. In general, we observe four strong positive long-term LPPLS-CI values. The first is observed in the US, and Canada, France, Germany, Italy, and the UK, from January 1973 to December 1974. This crash came on the heels of the collapse of the Bretton Woods system, and the devaluation of the U.S. dollar from the Smithsonian Agreement. Next, we observe a strong positive long-term LPPLS-CI value preceding ‘‘Black Monday’’ in October 1987 in the US, as well as in Canada, Japan, and the UK. A similar observation for the US, Canada, and the UK, as well as to some extent for Germany, can be made during the Asian Financial Crisis of

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[6] Figure A1 in the Appendix also presents the quantile-on-quantile relationships between the MS-LPPLS-CIs of the US and the *LGP*, based on the econometric framework of Sim and Zou (2015). As can be seen from the plots, unconditional quantiles of *LGP* tend to be negatively (positively) associated with the positive (negative) indicators, with very little variation across the size (quantiles) of *LGP*, thus providing further motivation to rely on a quantiles-based approach, rather than a quantile-on-quantile method. Intuitively, the sign of the plots make sense, as *LGP* captures risk, its higher values will speed up the crash and delay the recovery, thus reducing the positive MS-LPPLS-CIs, and increasing the negative indicators.

1997. We also see a clustering of highly positive LPPLS-CI values leading up to the Dot-com bubble burst over March 2000 to October 2002, especially for the US, along with Canada, France, Italy, and the UK, 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 Figure 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 observe pronounced LPPLS-CI values (positive and negative) at points where we detected the same for the long-term indicators. In addition, we see that strong positive medium-term LPPLS-CI values were formed before strong long-term LPPLS-CI values leading up to the GFC. In contrast, the short-term LPPLS-CI (green lines in Figure 1) uses 30 fits from fitting windows of size 30 to 90 observations. This represents just 1 month. As can be seen from Figure 1, this scale produces the most signals. It can also be inferred from the figure that the smallest crashes/rallies are signalled from this scale, possibly as these indicators pick 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 the volatility of an asset can be modelled as an increasing function of the square root of time, one can conclude that shorter time-scales are best-suited for detecting smaller crashes or rallies, while the medium and longer time-scales are best-suited for detecting larger crashes or rallies. This intuition is confirmed empirically by the patterns observed in Figure 2 wherein the long-term scale confidence indicators produce fewer signals but appear to capture larger crashes or rallies, while the shorter-scale indicators generate more frequent signals that precede smaller crashes or rallies. 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 in the case of the positive bubble indicator.

[INSERT FIGURE 2]

3.2. Comovement of Bubbles

Examining the computed confidence indicators across the different stock markets in Figure 2, we observe similar timing of strong (positive and negative) LPPLS-CI values between the US and the remaining six countries of the G7 bloc. This lends to the idea of synchronized boom and bust cycles of the seven developed equity markets. Indeed, the issue of synchronicity is statistically confirmed by Bayesian Gaussian graphical vector autoregressive (BGGVAR) models applied to each of the six multi-scale LPPLS-CIs associated with the G7 countries, i.e., each seven variable BGGVAR has one particular bubble indicator of the seven considered stock markets. The BGGVAR framework combines the time series chain graphical model concept of Abegaz and Wit (2013) with the Bayesian Gaussian Graphical Models outlined in Williams (2021).

In our application, the strength of the links in terms of a particular LPPLS-CI across the G7 markets in the BGGVAR can be assessed by computing the so-called partial direct correlations and partial contemporaneous correlations as measures of strength of the lagged and contemporaneous associations across the country-specific bubble indicators. Here, the partial contemporaneous correlation is defined as the correlation between the LPPLS-CIs of two countries at the same point in time after removing the linear effects of the other countries at the same point in time and all countries at previous times. As is known, the direct relationships among the variables across time are captured in the VAR model by the regression coefficients. In the BGGVAR framework, the strength of lagged associations between variables is captured by the so-called partial directed correlations. Specifically, in a VAR(1) setting that is adopted in our case based on the SIC, the partial direct correlations measure the linear association between a dependent variable, i.e., the LPPLS-CI of a particular country at time t and an explanatory variable (the LPPLS-CI of another country) at time $t-1$ after removing the linear effects of all other variables at time $t-1$. The partial direct correlations thus quantify the direct influence of an explanatory variable on the dependent variable.

Figure 3 presents the estimated partial contemporaneous and partial direct correlations under the six multiscale LPPLS-CIs involving the G7 countries. The green lines in the figures indicate lower (higher) positive correlations depending on the size of the line and lighter (darker) red lines indicate lower (higher) negative correlations. Panels A (D), B (E), C (F) present the findings for the short, medium and long-time scales for the positive (negative) bubble indicators. In each panel, partial contemporaneous are presented on the left and partial direct correlations are presented on the right. We observe in general stronger evidence of positive contemporaneous correlations for both the positive and negative bubble indicators compared to direct correlations. This is possibly due to bubbles being transmitted across countries within a week, i.e., instantaneously in the weekly time frame, rather than with a delay. While the close association of bubbles between the U.S. and Canada is observed, particularly at the short and medium time scales, we also observe strong bubble interactions within European markets as a block, involving Germany, France, Italy and the UK in particular. Interestingly, the US and UK exhibit strong connectedness in their long-term negative bubble indicators, while stronger cross-market associations of negative bubbles are observed at the short and medium time scales.

[INSERT FIGURE 3]

3.3. Gold-to-Platinum Price-Ratio and Predictability of Bubbles

Having estimated the bubble indicators and provided preliminary insight to the comovement of bubble patterns across markets, we proceed with our main focus that is the predictability of these bubbles as well as their interactions. To this end, motivated by the evidence on Huang and Kilic (2019) that the Gold-to-Platinum price ratio (*LGP*) captures the time-variation is risk and explains the cross-section of stock market returns, we next analyse the nature of predictability emanating from *LGP* to the short-, medium-, and long-term positive and negative bubble indicators of the US in particular, as well as the remaining six of the G7 countries. To further enlarge our understanding, motivated by the visual and statistical evidence from the BGGVAR analysis indicating strong evidence of synchronized boom and bust cycles of the seven developed equity markets, following Jackson et al. (2016), we estimated six dynamic factor models (DFM) involving the six bubble indicators associated with the G7 countries and derived the corresponding six common (global) factors associated with the bubble indicators. This allows us to examine the predictability of bubble comovements across the G7 markets through the extracted factors. This is an important consideration as detecting the role of *GP* in driving the commonality in movements of bubbles clearly has important implications for the alignment of monetary policies across the G7, particularly during financial market crises (Antonakakis et al., 2019).

For the sake of completeness and comparability with the nonparametric causality-in-quantiles framework, we first conduct several preliminary tests to further strengthen the case for our predictive model. Table 2 presents the findings from the linear Granger causality tests and tests of nonlinearity. In Panel A, we present the test statistic for the null hypothesis of no Granger causality running from the Gold-to-Platinum price ratio to the bubble indicators listed in each column in the top. As evident, the linear tests yield no indication of predictability running from *LGP* to the bubble indicators for the US, barring that of the short-term positive LPPLS-CI at the 5% level of significance.

[INSERT TABLE 2]

Having observed mostly insignificant evidence of causality based on the linear specification, we next examine whether the finding of non-causality might be due to model misspecification that assumes a linear predictability relationship. Therefore, in order to explore whether the linear model is misspecified, we next test for the presence of nonlinearity in the relationship between the six LPPLS-CIs and *LGP*. In this regard, we use the Brock et al. (1996, BDS) test on the residuals from the linear model used in the linear Granger causality test, and check whether the null hypothesis of *i.i.d.* residuals at various dimensions (*m*) can be rejected or not. Panel B presents the results of the BDS nonlinearity tests. As shown in the table, the BDS test yields overwhelming evidence of nonlinearity, that is, we reject the null hypothesis of linearity (*i.i.d.* residuals) at the highest level of significance, consistently across all six predictive cases considered. In sum, the BDS test confirms that the linear model is indeed misspecified due to the existence of uncaptured nonlinearity, and hence, further predictive inference must rely on a nonlinear model, which justifies our nonparametric causality-in-quantiles approach.

Next, we address the issue of instability in the linear model and potential misspecification by examining the presence of possible structural breaks in the relationship between *LGP* and stock market bubbles in the US. For this purpose, we utilize the powerful *UDmax* and *WDmax* tests multiple structural breaks as proposed by of Bai and Perron (2003) on the equations of the linear Granger causality test. Based on the results reported in Panel C of the table, we find that there is widespread evidence of regime changes, especially before, during or after the periods of major bubbles identified and discussed in Section 3.1. Given that the parameter estimates are indeed unstable over the full sample period, we conclude that the linear Granger causality results are invalid. To achieve accurate causal analysis in our context, we must rely on an econometric model that is inherently time-varying, which we accomplish through our quantiles-based nonlinear methodology.

In light of the presence of nonlinearity and regime changes in the relationship between *LGP* and the six LPPLS-CIs, our linear Granger causality results are clearly unreliable. This provides us with a strong statistical motivation to utilize the nonparametric causality-in-quantiles testing method, which can accommodate such misspecifications. Table 3 reports the quantile causality test statistics for causality running from the Gold-to-Platinum price ratio (Panel A) and risk aversion (Panel B) to the MS-LPPLS-CIs for a particular quantile listed in the first column. Examining the standard normal test statistics, derived from the quantiles-based results, over the range of 0.10 to 0.90, we can draw several important conclusions.

[INSERT TABLE 3]

Unlike the linear Granger causality findings reported in Table 2, the quantiles-based model, reported in Panel A, detects strong evidence of predictability from *LGP* over the entire quantile-limit considered on the multi-scale negative and positive bubbles indicators, at the 1% level of significance. The only exception is the highest considered quantile of 0.90 under the short-term positive LPPLS-CI, where causality is only detected at the 10% level of significance.[7] This suggests that bubbles are indeed predictable by measures of market uncertainty which is an important consideration for the implementation of risk mitigation mechanisms by policy makers. These findings also add support to the evidence in Demirer et al. (2019) that bubble formation can be predicted via market-based measures of risk and sentiment.

While predictability is generally stronger for negative bubbles than their positive counterparts, when we compare the values of the test statistics across the time scales, we find that the predictive impact is strongest for the long-term, followed by the medium- and short-term indicators for negative bubbles. However, in the case of the positive bubbles, causality is found to be strongest in the short-run (barring the quantile of 0.90), followed by the medium- and long-runs. This means that the Gold-to-Platinum price ratio serves as a more robust predictor of deeper downward accelerating price formations followed by a rally, i.e., long- and

[7] Recent studies have indicated that diamond, just like gold, performs the dual role of consumption and investment goods (see, for example, Caporale et al. (2022), Plastun et al. (2022)). In light of this, we also conducted the nonparametric causality-in-quantiles test to predict the MS-LPPLS-CIs with the logarithm of the Diamond-to-Platinum price ratio over the 1st week of January 2002 till the 2nd week of September 2020 (based on data availability, with diamond prices in US dollars obtained from Bloomberg). As can be observed from Table A1 in the Appendix, our findings are qualitatively similar to those obtained under *LGP* and *RA* (reported in Table 3).

medium-term negative bubbles. At the same time, *LGP* can also provide early signals of possible severe forthcoming crashes from accelerating prices by strongly predicting short-term positive bubbles, which tend to lead the medium- and long-run positive LPPLS-CIs as pointed out in Figure 2 and discussed in Section 3.1.

As a matter of robustness check, we utilize the measure of risk aversion (*RA*) of Bekaert et al. (2022) as an alternative predictor of bubbles. Bekaert et al. (2022) develop a new measure of time-varying risk aversion that ultimately can be calculated from observable financial information at the daily frequency. This metric relies on a set of six financial instruments namely, the term spread, credit spread, a de-trended dividend yield, realized and risk-neutral equity return variance and realized corporate bond return variance. An important feature of this measure is that it distinguishes time variation in economic uncertainty (the amount of risk) from time variation in risk aversion (the price of risk) and, thus, provides an unbiased representation for time-varying risk aversion based on a utility function in the hyperbolic absolute risk aversion (HARA) class.[8] As seen in Panel B of Table 3, we obtain qualitatively similar results, including that of the asymmetric behaviour, as under the *LGP*. This finding confirms the robustness of our results regarding the predictability of bubble formation due to measures of market risk or sentiment when an alternative metric of risk in the financial system is employed.

Reverting to the utilization of the Gold-to-Platinum price ratio, we present in Table 4 the quantile causality test statistics for causality running from *LGP* to the MS-LPPLS-CIs for a particular quantile listed in the first column. Panels A through F report the findings for the bubble indicators for each G7 economy and Panel G reports the same for the factors derived from the DFM applied to the G7 MS-LPPLS-CIs. We find that the predictability patterns across the six bubbles indicators of the remaining six of the G7 bloc remain quite consistent and significant, along with country-specific asymmetries, at least at the 5% level of significance. Specifically speaking, only 9 cases (at the highest quantile of 0.90) out of the possible 324 remain not predictable by the global risk metric, while we observe strong evidence of bubble predictability in all other cases. Accordingly, the evidence suggests that the Gold-to-Platinum

[8] The daily index, which we average over weeks, is available for download from: https://www.nancyxu.net/risk-aversion-index.

price ratio can not only predict bubble dynamics for the US market, but also that of Canada, France, Germany, Italy, Japan and the UK.[9]

Given the evidence that *LGP* has a strong causal influence on the stock market bubbles of all G7 countries individually, we next examine predictability patterns based on the six extracted factors from the DFM as discussed earlier. Examining the results reported in Panel G, not surprisingly, the factors are found to be strongly predictable via *LGP* at the 1% level of significance, consistently over the entire coverage of their respective conditional distributions, i.e., quantiles of 0.10 to 0.90.[10] As the factors capture the dynamics behind the common movements of bubbles of the G7, we can derive that, in general, *LGP* have stronger predictive impact on positive long-term bubbles, compared to the medium- and short-runs, and hence can predict the synchronized common equity market crashes that are likely to follow after overheating of markets. The conclusions are similar when it comes to negative bubbles, however with some exceptions around the median, i.e., barring relatively normal-sized commoving less severe downturns before recovery.

[INSERT TABLE 4]

Overall, our analysis shows that the link between stock market bubbles in the US and *LGP* is non-linear and regime dependent, resulting in very weak evidence of causality if tested within a linear causality framework. However, by using a non-parametric econometric framework that accounts for the nonlinear and state-specific features embedded in the data, we find strong evidence of predictability stemming from *LGP*, with certain degree of asymmetry in terms of the strength of predictability across the time-scale and sign of the bubbles (and also to some extent dependent on their size). The results also carry over to the rest of the G7 bloc (with country-specific differences), and hence, the synchronization of the bubbles in these economies. Clearly, our findings provide a valuable opening for market regulators as the results

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[9] Though the focus is on developed equity markets, we also conducted a similar analysis on the bubble indicators of five important emerging countries namely, Brazil, China, India, Russia and South Africa, i.e., the BRICS bloc, over the 2nd week of February 1999 to the 2nd week of September 2020, with the MS-LPPLS-CIs plotted in Figure A2 in the Appendix. As reported in Panels A through E in Table A2 in the Appendix, *LGP* also contains very strong predictive ability, barring 9 (at the upper most quantile of 0.90) of the possible 270 cases, for the six LPPLS-CIs of the 5 BRICS stock markets.

[10] In light of the MS-LPPLS-CIs picking up bubble episodes for the BRICS that align with those of the G7 during the common period of 1999-2020 (see Figures 1 and A2 in the Appendix, with the BGGVAR results available upon request from the authors), in Panel F of Table A2 in the Appendix, we report the nonparametric causality-in-quantiles test results from *LGP* on to the six common factors extracted from the DFM applied to the 12 countries for each of the six bubbles indicators. Again, as with the case for the G7, *LGP* is able to explain the common movement of bubbles across the G7 and BRICS over the entire quantile range of 0.10 to 0.90 at the 1% level of significance. This result is not surprising in light of the evidence provided by Demirer et al. (2018) of the role of global risk aversion in explaining the comovements of emerging markets with respect to the US.

show that the readily available metric of market risk based on the gold to platinum prices can be used to model and monitor the occurrence of bubble patterns in financial markets as well as the connectedness of these bubbles across the global markets. This evidence indicates that the accuracy of forecasting models for boom and bust market conditions can be improved by incorporating this risk metric which is available at both the high and low frequencies in various applications ranging from market monitoring mechanisms to the valuation of derivatives and the computation of downside risk proxies for the financial system.

4. Conclusion

While a large literature has been devoted to modeling and detecting bubbles in financial markets, the predictability of bubbles and the connectedness of bubbles across markets is relatively understudied. The primary objective of this paper is to analyse the predictive impact of a readily available metric of risk namely, the gold to platinum price ratio on equity market bubbles in the US and the rest of G7 bloc. To this end, we first employ the popularly utilized Log-Periodic Power Law Singularity (LPPLS) model to detect positive and negative bubbles via the Multi-Scale LPPLS Confidence Indicator (MS-LPPLS-CI) approach. Our findings reveal the ability of these indicators to detect major crashes and rallies, suggesting that the shorter time scale indicators are best suited for detecting smaller crashes or rallies, while the medium and longer time scale indicators are best suited for detecting larger crashes or rallies. Further extending our analysis to a predictive context, we utilize a nonparametric causality-in-quantiles test to assess the causal linkages between the gold to platinum price ratio (*LGP*) and the estimated bubble indicators. Our results demonstrate strong evidence of predictability for the conditional distributions of the LPPLS-CIs, particularly for the occurrence of short-term positive and long-term negative bubble. While the predictive power of LGP over bubbles extends to the six other developed stock markets in the G7 bloc, our findings also yield evidence of synchronized boom and bust cycles across equity markets in the G7 bloc and that *LGP* can also predict the common component of bubbles based on the common factors extracted from the bubble indicators for the G7.

The evidence of predictability in bubble dynamics across the different markets examined should be of immense value to investors in designing state-specific portfolios in country diversification strategies (van Eyden et al., 2023). Furthermore, as bubbles are associated with real economic activity, carrying significant welfare implications, our results are of paramount importance to policymakers in devising appropriate policy responses to mitigate the destabilizing effects of bubbles and subsequent crashes. At the same time, given that the common component of bubbles is predictable by *LGP*, we also provide a tentative argument in favour of monetary policy synchronization across the G7 to deal with the potentially destabilizing effects of bubbles (Caraiani et al., 2023; Gupta et al., 2023), despite the evidence of heterogeneous country-level responses of the LPPLS-CIs to global risk. It must, however, be noted that while we do find strong evidence of predictability from the gold-to-platinum price-ratio over the stock market bubbles of the G7, the stronger effects observed at lower conditional quantiles of the bubble indicators may indicate that other factors contribute to the formation of bubbles that we cannot control for in our study due to the bivariate structure of our econometric model. In this context, for future work, it would be worthwhile to explore the role of conventional and unconventional monetary policy shocks on the conditional distribution of bubbles, contingent on the state of the global risk factor as captured by *LGP* (see, for example, the discussions in Çepni and Gupta, 2021l and Çepni et al., 2021).

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Compliance with Ethical Standards

Conflicts of interest

Authors have no conflict of interest.

Ethics approval

Not applicable.

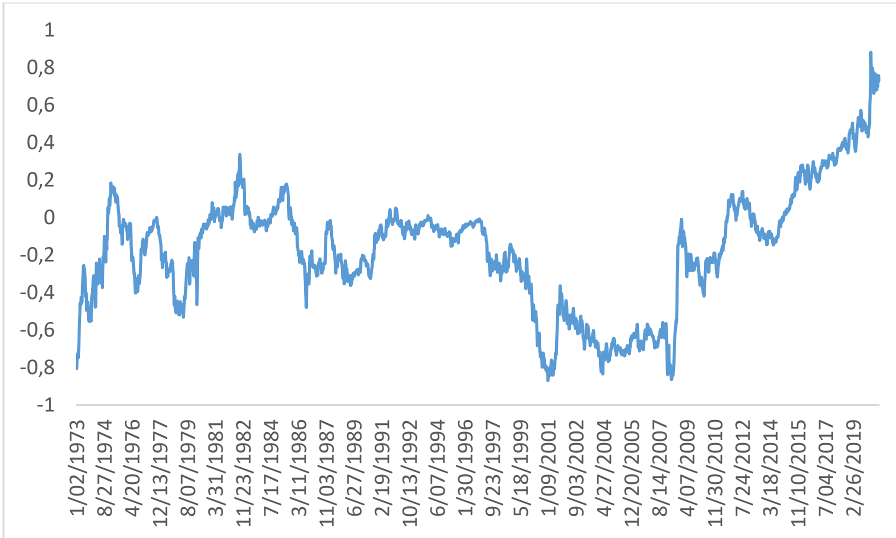
Consent to participate

Not applicable.

Consent for publication

Not applicable.

Figure 1: Natural Logarithm of Gold-to-Platinum Price Ratio (*LGP*)



Note: The figure shows the natural logarithm of the ratio of gold to platinum prices (LGP) on a weekly frequency for the period from January 1973 to the 2nd week of (13th) September, 2020.

Figure 2: Multi-Scale Log-Periodic Power Law Singularity Confidence Indicators (MS-LPPLS-CIs) of the G7 Countries.

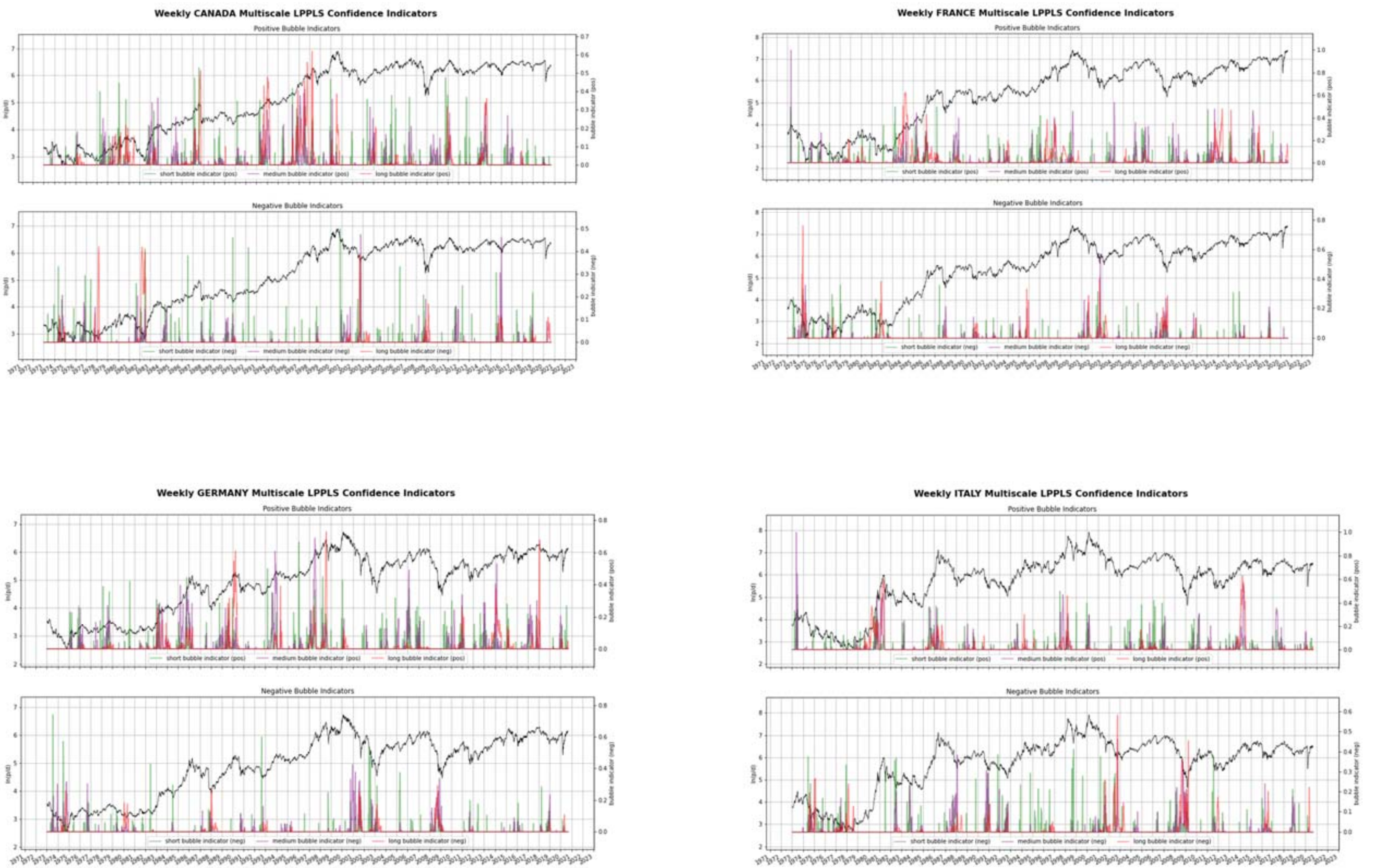
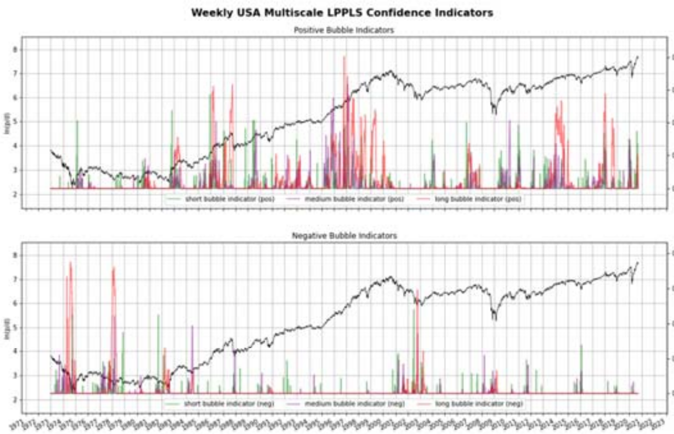
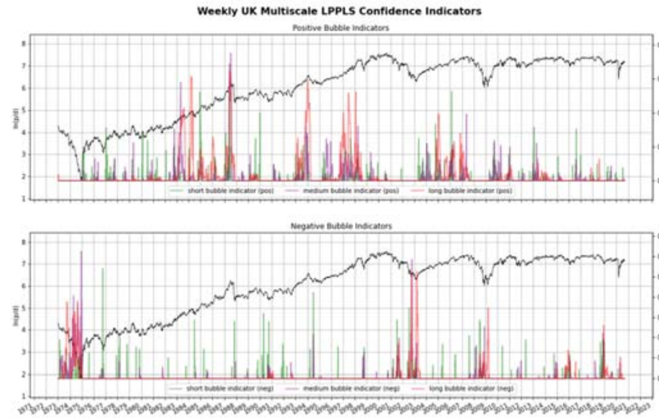


Figure 2 (continued)





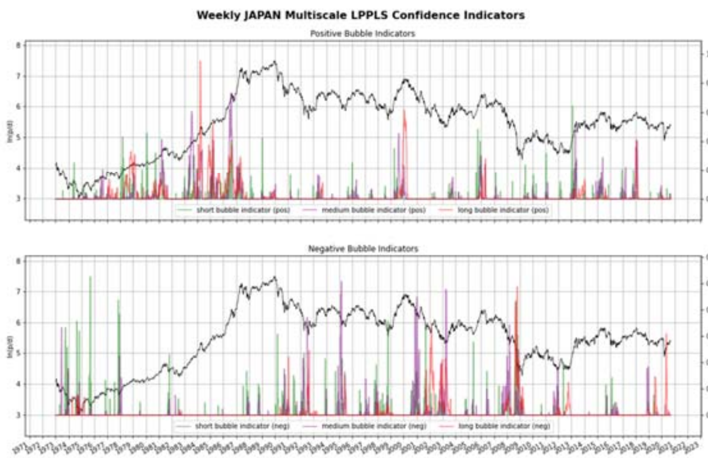
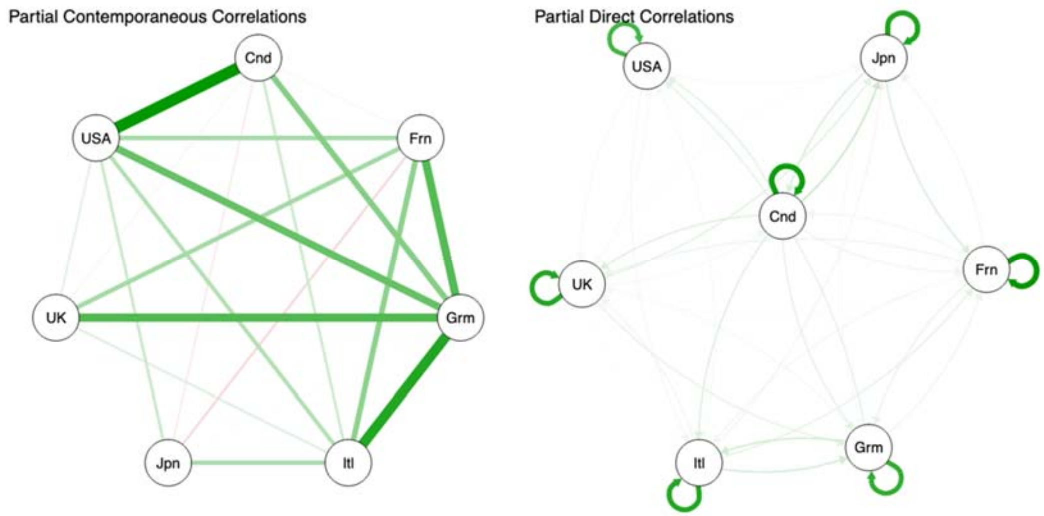
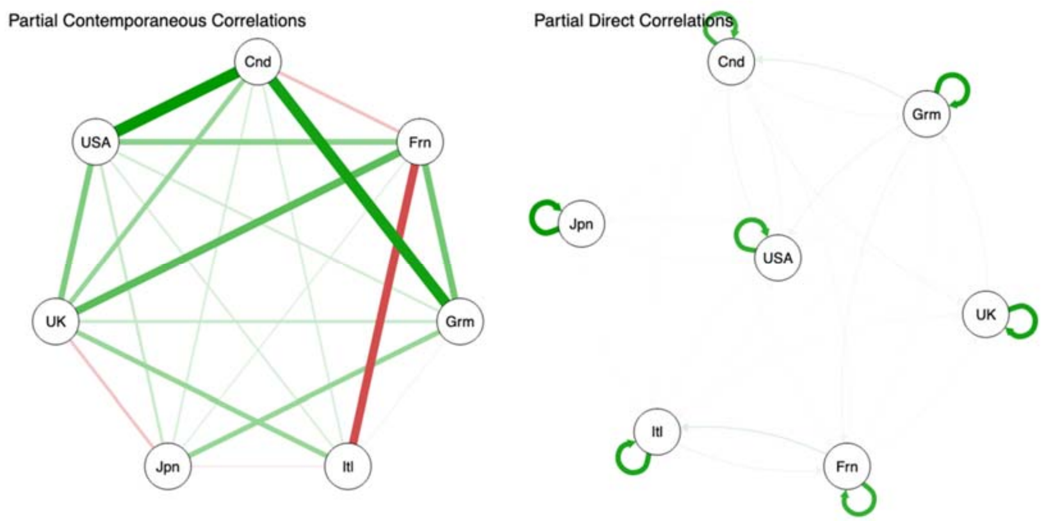


Figure 3: Spillover results from the Bayesian Gaussian Graphical Vector Autoregressive Models (BGGVARs) of the MS-LPPLS-CIs for the G7.

Panel A: *Positive Short-Term*



Panel B: *Positive Medium-Term*



Panel C: *Positive Long-Term*

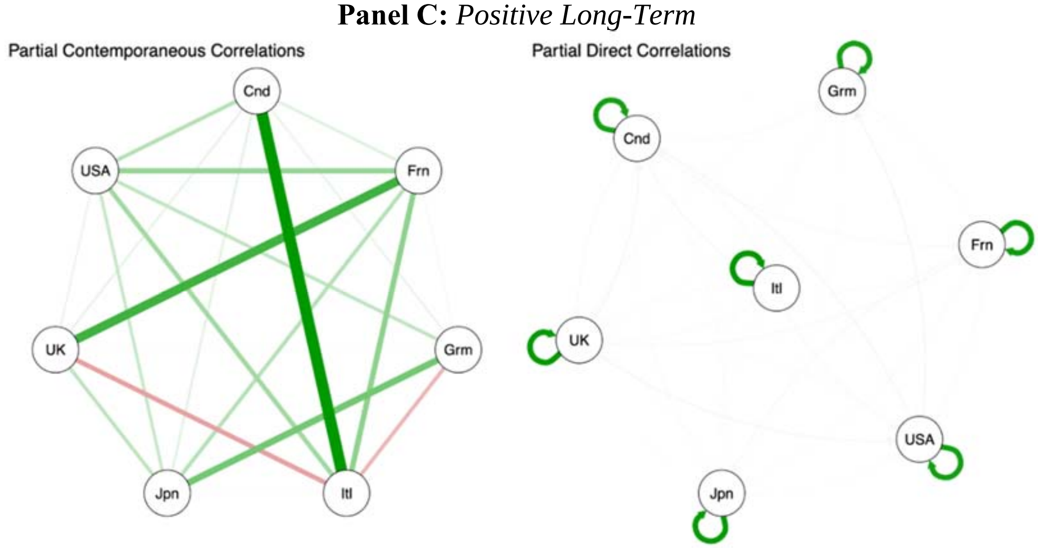
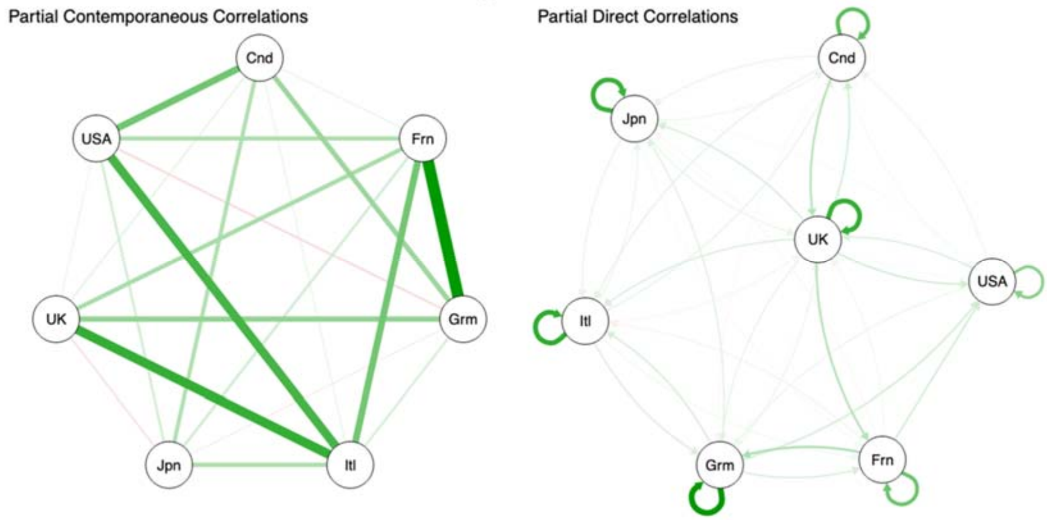
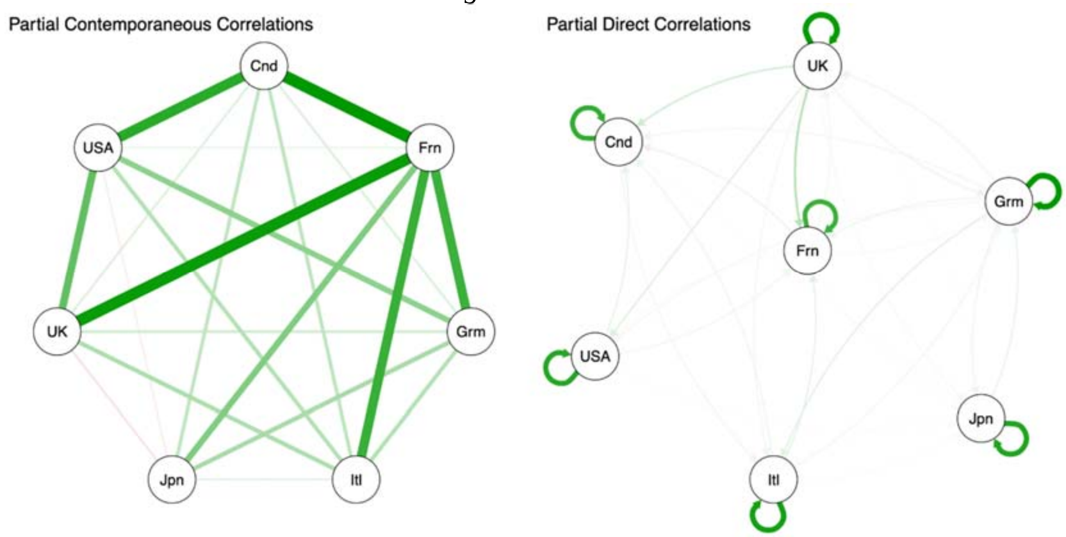


Figure 3 continued.

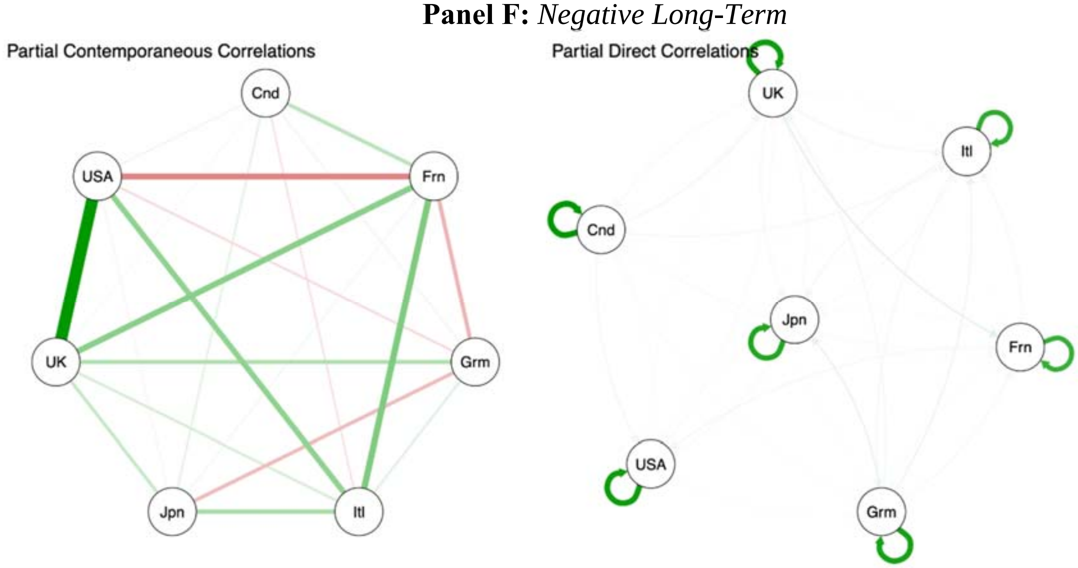
Panel D: *Negative Short-Term*



Panel E: *Negative Medium-Term*



Panel F: *Negative Long-Term*



Note: Cnd: Canada; Frn: France; Grm: Germany; Itl: Italy; Jpn: Japan; UK: The United Kingdom; USA: The United States of America. Lighter (Darker) Green lines indicate lower (higher) positive correlations; Lighter (Darker) Red lines indicate lower (higher) negative correlations.

Table 1: Summary Statistics for the US Data

	Positive bubbles			Negative bubbles			
Statistic	Short-Term	Med.-Term	Long-Term	Short-Term	Med.-Term	Long-Term	LGP
Mean	0.013	0.020	0.041	0.005	0.006	0.013	-0.171
Median	0.000	0.000	0.000	0.000	0.000	0.000	-0.119
Maximum	0.571	0.635	0.806	0.480	0.443	0.750	0.882
Minimum	0.000	0.000	0.000	0.000	0.000	0.000	-0.870
Std. Dev.	0.048	0.059	0.102	0.028	0.028	0.074	0.314
Skewness	5.388	5.278	3.289	9.814	8.073	7.520	0.006
Kurtosis	38.416	38.352	14.455	126.815	89.655	62.689	3.076
Jarque-Bera	142119.5***	141164.2***	18096.41***	1629808***	805790.3***	392941.5***	0.617
Observations	2489	2489	2489	2489	2489	2489	2489

Note: Std. Dev. stands for standard deviation; the null hypotheses of the Jarque-Bera test corresponds to the null of normality; LGP is the natural log of Gold-Platinum price ratio. *** indicates rejection of the null hypothesis at a 1% level of significance.

Table 2: Linear Granger Causality and Nonlinearity Tests for the US

	Positive bubbles			Negative bubbles		
	Short-Term	Med.-Term	Long-Term	Short-Term	Med.-Term	Long-Term
			Panel A: Linear Granger Causality Tests			
LGP	5.503**	2.121	1.093	2.498	1.076	0.065
			Panel B: Brock et al. (1996) BDS test of non-linearity			
m=2	29.703***	29.079***	32.436***	59.805***	49.870***	63.690***
m=3	31.440***	33.652***	38.494***	61.972***	53.167***	67.288***
m=4	32.907***	36.674***	43.049***	64.744***	56.123***	72.158***
m=5	35.116***	40.416***	47.743***	69.138***	60.321***	79.199***
m=6	37.566***	44.596***	53.236***	74.951***	66.237***	88.678***
			Panel C: Break Dates			
	2/11/1986	9/02/1980, 5/09/1989, 4/01/1997, 5/25/2004, 4/03/2012	10/13/1987, 8/30/1994, 6/01/1999, 10/31/2006, 7/08/2014	3/23/1982, 4/07/1992, 7/09/2002, 2/11/2003, 9/01/2009	5/20/1980, 12/15/1987, 2/07/1995, 10/29/2002, 10/18/2011	3/04/1980, 1/05/1988, 8/08/1995, 10/22/2002, 12/15/2009

Note: In Panel A, the entries correspond to $\chi^2(1)$ test statistic of the null hypothesis of no Granger causality running from the gold to platinum ratio (LGP) to the bubble indicators listed in each column in the top. ** indicates rejection of the null hypothesis at a 5% level of significance. In Panel B, the entries correspond to the *z*-statistic of the Brock et al. (1996) BDS test of non-linearity with the null of *i.i.d.* residuals across various dimensions (*m*). The test is applied to the residuals recovered from the MS-LPPLS-CI equation with one lag each of the bubble indicators listed in each column and *LGP*. *** indicates rejection of the null hypothesis at 1% level of significance. In Panel C, the entries correspond to the dates of structural breaks based on the Bai and Perron (2003) the test applied to the MS-LPPLS-CI equation with one lag each of the bubble indicators and *LGP*.

Table 3: Causality-in-Quantiles Test Results for the US.

	Positive bubbles			**Negative bubbles**		
	Short-Term	Med.-Term	Long-Term	Short-Term	Med.-Term	Long-Term
Quantile	**Panel A:** Causality from *Gold to Platinum* ratio to bubble indicators					
0.10	3598.178^{***}	1572.357^{***}	930.690^{***}	2373.595^{***}	3741.828^{***}	3917.066^{***}
0.20	2056.986^{***}	866.102^{***}	524.683^{***}	1350.177^{***}	2147.639^{***}	2324.079^{***}
0.30	1317.134^{***}	540.098^{***}	333.199^{***}	877.434^{***}	1393.105^{***}	1547.770^{***}
0.40	855.884^{***}	345.303^{***}	215.176^{***}	587.508^{***}	925.306^{***}	1035.379^{***}
0.50	537.853^{***}	210.668^{***}	135.879^{***}	388.022^{***}	606.670^{***}	691.676^{***}
0.60	311.388^{***}	116.821^{***}	81.230^{***}	243.378^{***}	375.271^{***}	433.356^{***}
0.70	151.882^{***}	55.239^{***}	42.387^{***}	136.939^{***}	199.706^{***}	241.846^{***}
0.80	48.819^{***}	16.057^{***}	15.333^{***}	60.577^{***}	83.414^{***}	104.573^{***}
0.90	1.684^{*}	2.616^{***}	3.115^{***}	12.045^{***}	13.149^{***}	23.000^{***}
Quantile	**Panel B:** Causality from *Risk Aversion* ratio to bubble indicators					
0.10	2497.302^{***}	1921.564^{***}	1726.158^{***}	3060.507^{***}	2937.171^{***}	3103.233^{***}
0.20	1467.991^{***}	1086.085^{***}	995.513^{***}	1798.578^{***}	1717.865^{***}	1827.015^{***}
0.30	925.752^{***}	682.312^{***}	638.115^{***}	1188.045^{***}	1122.589^{***}	1210.217^{***}
0.40	610.687^{***}	436.605^{***}	414.084^{***}	803.399^{***}	748.887^{***}	821.887^{***}
0.50	381.619^{***}	422.316^{***}	260.159^{***}	532.879^{***}	490.742^{***}	550.385^{***}
0.60	218.932^{***}	141.959^{***}	152.721^{***}	336.645^{***}	308.434^{***}	352.343^{***}
0.70	104.549^{***}	63.641^{***}	76.051^{***}	190.543^{***}	170.823^{***}	204.400^{***}
0.80	33.873^{***}	15.423^{***}	24.922^{***}	85.445^{***}	77.963^{***}	97.543^{***}
0.90	0.568	1.966^{**}	5.981^{***}	18.505^{***}	15.645^{***}	25.314^{***}

Note: The table reports the quantile causality test statistics for causality running from the gold to platinum price ratio (Panel A) and risk aversion (Panel B) to the MS-LPPLS-CIs for a particular quantile listed in the first column. *** and * indicate rejection of the null hypothesis of no Granger causality at the 1% and 10% levels of significance respectively (critical values of 2.575 and 1.645).

Table 4: Causality-in-Quantiles Test Results for the Remaining G7 Countries.

	Positive bubbles			**Negative bubbles**		
	Short-Term	Med.-Term	Long-Term	Short-Term	Med.-Term	Long-Term
Quantile			**Panel A:** Canada			
0.1	1749.396***	2795.763***	1672.209***	3920.845***	3618.584***	3882.465***
0.2	985.644***	1564.432***	949.203***	2265.182***	2066.876***	2311.245***
0.3	632.441***	987.150***	605.843***	1476.550***	1332.426***	1528.235***
0.4	416.144***	636.396***	396.602***	985.328***	883.295***	1026.098***
0.5	268.001***	397.890***	251.811***	644.676***	578.808***	676.708***
0.6	161.573***	218.149***	154.251***	397.199***	347.794***	425.370***
0.7	84.673***	97.996***	80.629***	215.993***	181.152***	238.757***
0.8	31.733***	30.371***	29.109***	88.497***	74.418***	106.765***
0.9	2.835***	0.476	3.362***	13.726***	9.820***	22.706***
			Panel B: France			
0.1	3663.161***	2195.522***	2520.415***	4112.495***	2440.374***	2211.884***
0.2	2096.065***	1215.179***	1460.261***	2393.519***	1385.056***	1260.551***
0.3	1337.887***	766.728***	948.153***	1564.446***	897.814***	824.607***
0.4	863.363***	491.242***	602.753***	1044.078***	599.371***	554.563***
0.5	544.901***	301.866***	369.633***	681.600***	394.445***	368.24***
0.6	323.092***	170.000***	207.634***	417.810***	245.713***	233.175***
0.7	164.779***	79.301***	99.070***	224.998***	137.137***	133.83***
0.8	60.428***	24.721***	25.147***	92.740***	59.813***	63.204***
0.9	4.228***	0.945	0.335	16.156***	11.056***	15.415***
			Panel C: Germany			
0.1	2185.375***	2714.982***	2840.062***	599.732***	1643.077***	3849.152***
0.2	1228.579***	1534.178***	1647.197***	339.768***	933.448***	2278.464***
0.3	786.794***	999.170***	1094.682***	220.677***	605.777***	1503.798***
0.4	516.595***	646.776***	720.507***	147.988***	404.920***	1010.292***
0.5	331.761***	390.885***	447.925***	98.124***	266.823***	661.674***
0.6	199.172***	215.039***	264.854***	62.027***	166.804***	411.573***
0.7	103.569***	94.323***	134.419***	35.467***	93.589***	234.005***
0.8	38.044***	22.126***	41.853***	16.375***	41.018***	100.309***
0.9	2.917***	0.129	0.316	4.152***	8.019***	18.771***
			Panel D: Italy			
0.1	3795.257***	3170.625***	2716.214***	3929.738***	3549.121***	3353.286***
0.2	2183.524***	1835.539***	1585.431***	2273.877***	2038.972***	1961.600***
0.3	1403.632***	1184.583***	1018.222***	1477.107***	1326.246***	1294.516***
0.4	914.751***	779.118***	666.968***	978.294***	875.444***	867.615***
0.5	577.383***	493.402***	424.787***	631.946***	570.577***	560.597***
0.6	345.023***	288.255***	255.411***	381.143***	342.722***	337.982***
0.7	180.002***	145.202***	137.413***	200.069***	182.403***	181.823***
0.8	66.604***	46.880***	50.225***	77.528***	71.028***	69.445***
0.9	5.875***	1.158	3.852***	8.870***	7.596***	7.472***

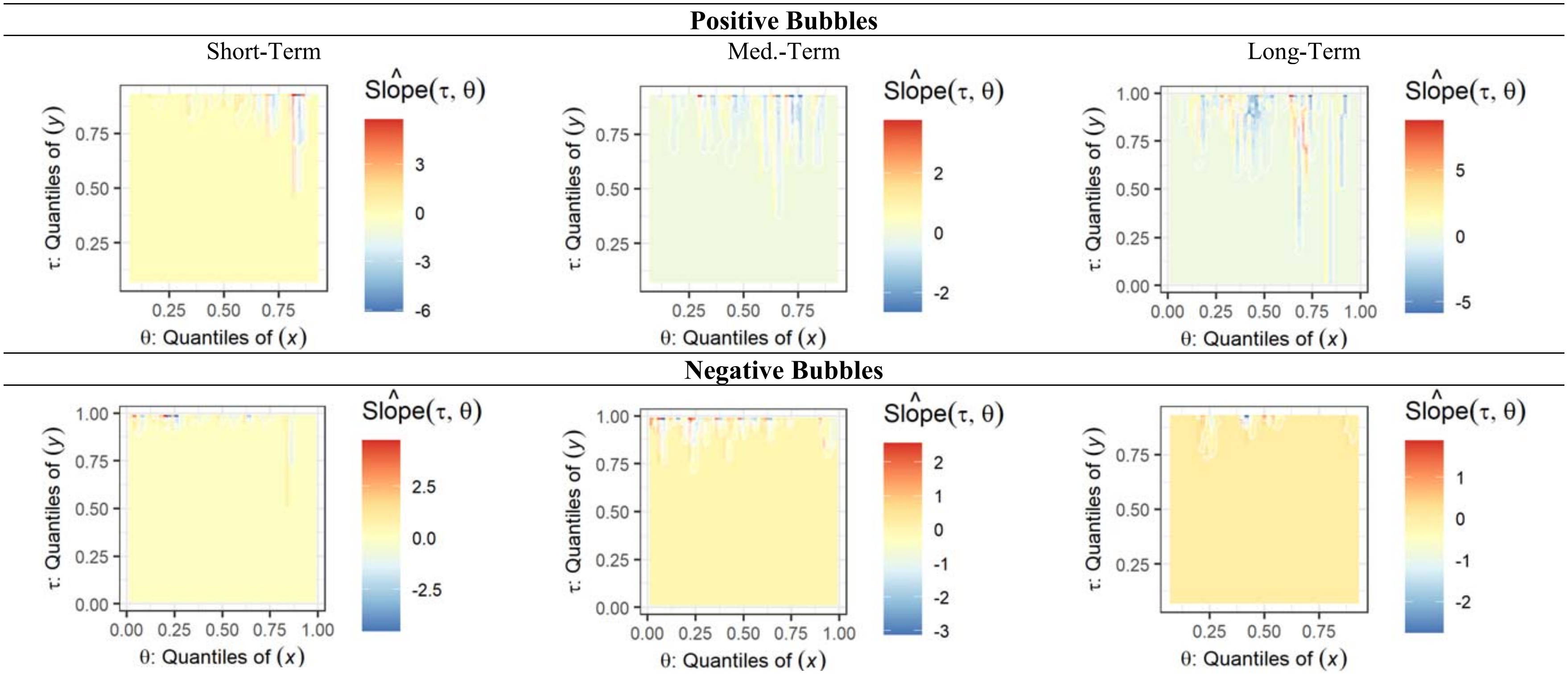
Table 4 (Continued)

			Panel E: Japan			
0.1	1828.492***	2833.291***	2574.343***	3986.522***	3383.210***	3140.639***
0.2	1029.709***	1621.235***	1491.503***	2309.169***	1918.305***	1804.947***
0.3	660.563***	1078.545***	947.964***	1506.216***	1240.307***	1176.739***
0.4	434.583***	709.528***	609.711***	1004.646***	813.528***	783.129***
0.5	279.846***	435.279***	373.207***	656.291***	513.055***	512.183***
0.6	168.703***	243.800***	216.896***	403.135***	308.315***	318.194***
0.7	88.430***	121.407***	110.070***	218.192***	151.844***	180.751***
0.8	33.149***	34.898***	33.717***	89.342***	56.418***	78.151***
0.9	2.926***	0.111	2.640***	13.594***	3.616***	14.007***
			Panel F: UK			
0.1	3813.723***	2776.656***	2399.110***	2127.266***	3584.691***	3781.795***
0.2	2194.842***	1546.219***	1460.148***	1211.981***	2056.473***	2229.995***
0.3	1411.759***	990.036***	933.293***	789.151***	1338.944***	1470.986***
0.4	920.915***	641.985***	598.732***	529.738***	895.910***	984.519***
0.5	581.104***	389.647***	366.592***	351.130***	587.098***	644.617***
0.6	338.868***	215.791***	206.253***	221.483***	360.264***	409.096***
0.7	172.541***	97.601***	94.544***	125.889***	198.971***	226.496***
0.8	59.191***	24.151***	24.480***	57.007***	84.343***	96.342***
0.9	3.857***	0.007	0.001	12.598***	14.197***	22.220***
			Panel G: MS-LPPLS-CI Factors of the G7			
0.1	5.355***	4.763***	8.954***	6.050***	6.635***	9.645***
0.2	7.137***	5.916***	12.452***	7.313***	8.295***	8.817***
0.3	6.408***	7.285***	15.294***	8.885***	8.485***	6.137***
0.4	6.503***	5.081***	16.184***	7.833***	7.653***	4.363***
0.5	6.846***	4.080***	16.528***	6.078***	7.312***	4.704***
0.6	6.169***	3.976***	16.481***	5.187***	6.660***	5.577***
0.7	5.863***	4.695***	15.573***	5.438***	6.536***	6.752***
0.8	5.444***	5.226***	12.914***	5.187***	6.774***	7.338***
0.9	4.226***	3.885***	9.089***	4.292***	5.191***	6.565***

Note: The table reports the quantile causality test statistics for causality running from the gold to platinum price ratio (LGP) to the MS-LPPLS-CIs for a particular quantile listed in the first column. Panels A through F report the findings for the bubble indicators for each G7 economy and Panel G reports the same for the factors derived from the DFM applied to the G7 MS-LPPLS-CIs. *** and * indicate rejection of the null hypothesis of no Granger causality at the 1% and 10% levels of significance respectively (critical values of 2.575 and 1.645).

APPENDIX

Figure A1: Quantiles-on-Quantiles Impact (Slope) of LGP on the MS-LPPLS-CIs for the US.



Note: The figures plot the quantile-on-quantile slope parameters where the dependent variable is the MS-LPPLS-CIs and the independent variable is the Gold to Platinum price ratio (*LGP*).

Figure A2: Multi-Scale Log-Periodic Power Law Singularity Confidence Indicators (MS-LPPLS-CIs) of the BRICS Countries.

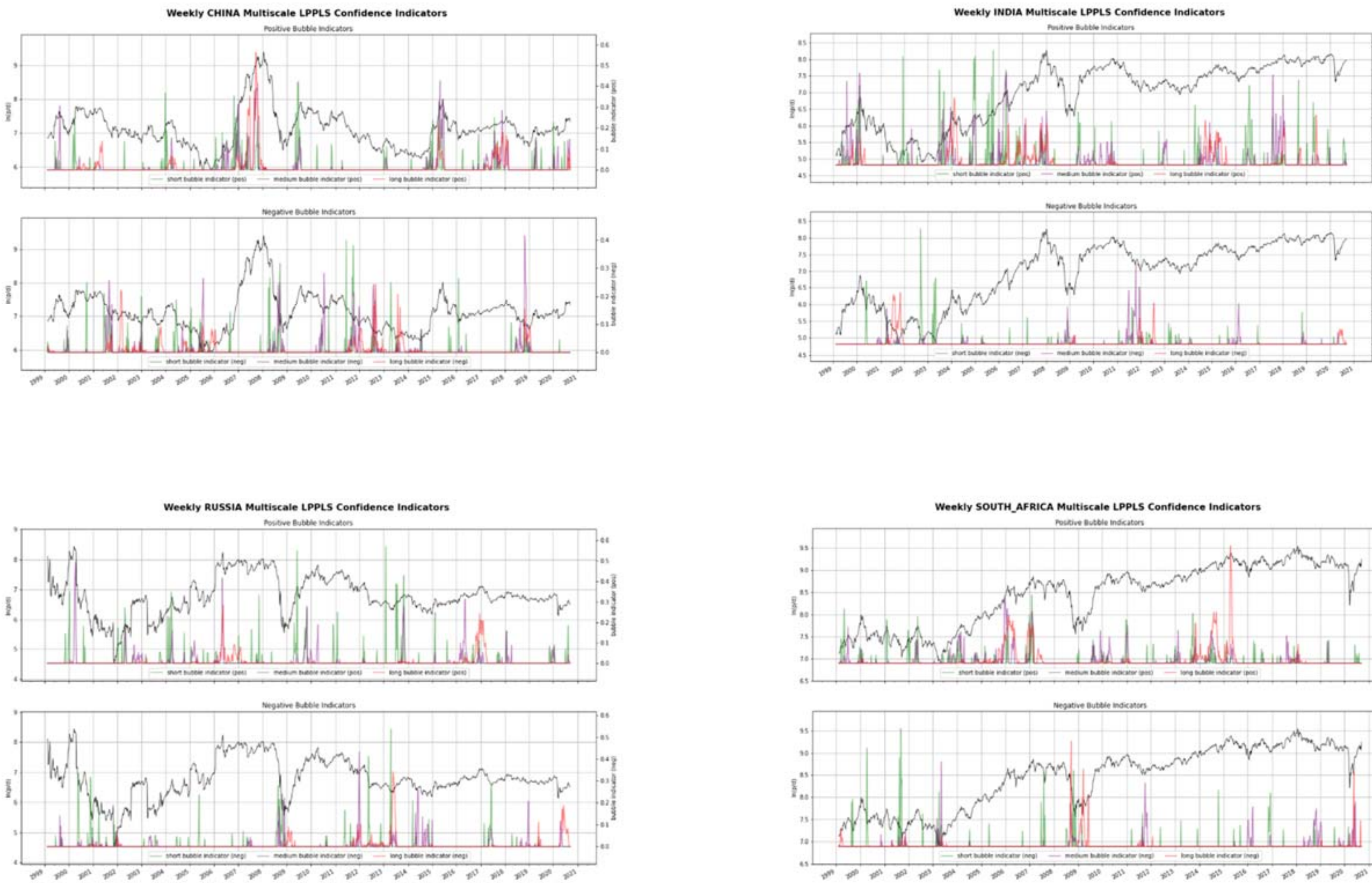


Table A1: Diamond to Platinum price ratio and bubbles.

	Positive bubbles			Negative bubbles		
	Short-Term	Med.-Term	Long-Term	Short-Term	Med.-Term	Long-Term
Quantile	Causality from *Diamond to Platinum* ratio to bubble indicators					
0.10	1369.604***	795.227***	961.955***	1234.818***	863.111***	693.244***
0.20	778.262***	431.515***	571.099***	705.753***	490.714***	395.354***
0.30	492.134***	263.621***	359.412***	460.649***	319.714***	258.820***
0.40	313.410***	167.316***	226.370***	310.104***	215.149***	175.387***
0.50	197.064***	97.619***	135.645***	206.348***	143.265***	117.979***
0.60	113.647***	49.994***	75.977***	130.927***	91.087***	76.334***
0.70	54.486***	21.572***	34.357***	75.175***	52.528***	45.261***
0.80	18.873***	6.258***	8.846***	34.797***	24.524***	22.527***
0.90	0.581	2.951***	1.012	8.394***	6.150***	6.986***

Note: The table reports the quantile causality test statistics for causality running from the diamond to platinum price ratio to the MS-LPPLS-CIs for the U.S. stock market for a particular quantile listed in the first column. *** indicate rejection of the null hypothesis of no Granger causality at the 1% level of significance (critical value of 2.575).

Table A2: Causality-in-Quantiles Test Results for the BRICS.

	Positive bubbles			Negative bubbles		
	Short-Term	Med.-Term	Long-Term	Short-Term	Med.-Term	Long-Term
Quantile	**Panel A:** Brazil					
0.1	1226.221***	1121.471***	918.602***	1789.527***	1681.006***	860.709***
0.2	689.844***	627.201***	521.376***	1035.089***	965.592***	490.103***
0.3	441.975***	406.720***	335.504***	670.244***	624.058***	318.772***
0.4	290.332***	261.225***	221.441***	441.284***	410.967***	213.109***
0.5	186.576***	161.994***	144.311***	283.502***	267.340***	140.328***
0.6	112.117***	92.268***	90.382***	172.165***	159.735***	87.747***
0.7	58.430***	46.069***	50.788***	92.535***	82.150***	49.280***
0.8	21.777***	13.781***	22.414***	35.907***	34.751***	22.966***
0.9	1.909*	0.484	5.959***	5.576***	4.691***	6.244***
	Panel B: China					
0.1	843.300***	771.534***	1556.874***	1753.979***	1550.746***	1309.085***
0.2	476.804***	434.436***	915.935***	1011.985***	881.909***	745.281***
0.3	307.171***	278.703***	594.560***	653.021***	563.594***	474.116***
0.4	203.215***	183.550***	401.634***	427.855***	372.420***	311.865***
0.5	131.916***	118.329***	256.708***	271.736***	239.385***	190.711***
0.6	80.555***	72.217***	154.403***	159.315***	139.262***	109.224***
0.7	43.231***	38.703***	84.712***	81.762***	68.653***	57.171***
0.8	17.215***	15.396***	36.023***	30.955***	23.146***	19.948***
0.9	2.219**	2.187**	6.626***	3.286***	0.924	0.303
	Panel C: India					
0.1	1312.056***	1069.461***	1246.480***	1165.953***	1013.816***	1836.750***
0.2	736.882***	589.210***	710.988***	664.037***	573.954***	1087.162***
0.3	470.073***	370.422***	456.322***	431.858***	370.114***	717.425***
0.4	306.717***	240.378***	293.393***	289.305***	245.033***	489.886***
0.5	195.073***	145.802***	180.472***	191.149***	159.122***	323.468***
0.6	115.228***	79.521***	101.803***	119.955***	97.300***	204.135***
0.7	58.086***	40.672***	50.438***	67.567***	52.627***	114.785***
0.8	20.035***	11.586***	15.232***	30.014***	21.773***	51.534***
0.9	1.315	0.837	1.319	6.220***	3.072***	11.687***
	Panel D: Russia					
0.1	1703.913***	1512.46***	1385.638***	882.256***	1102.025***	1667.775***
0.2	979.392***	856.119***	792.838***	501.968***	621.821***	977.267***
0.3	633.686***	545.145***	512.356***	325.949***	399.571***	653.100***
0.4	418.463***	357.389***	340.849***	217.937***	263.375***	433.793***
0.5	269.609***	230.445***	225.110***	143.631***	170.020***	282.310***
0.6	162.094***	140.172***	145.843***	89.801***	102.997***	170.291***
0.7	84.813***	77.587***	83.239***	50.269***	54.513***	91.824***
0.8	32.277***	27.044***	36.274***	22.006***	22.146***	38.814***
0.9	3.651***	1.832*	7.073***	4.275***	2.826***	5.794***

Table A2 (Continued)

			Panel E: South Africa			
0.1	1095.911***	1175.929***	1225.503***	1792.013***	1504.051***	1032.865***
0.2	614.968***	650.968***	746.588***	1035.224***	859.879***	592.108***
0.3	392.711***	410.822***	473.612***	677.667***	560.037***	387.720***
0.4	256.731***	271.677***	305.502***	455.804***	375.498***	262.000***
0.5	163.773***	166.398***	185.522***	302.050***	248.721***	175.207***
0.6	97.247***	91.839***	105.295***	190.042***	156.204***	111.988***
0.7	49.510***	42.351***	55.880***	107.357***	88.693***	65.393***
0.8	17.263***	13.293***	17.381***	47.897***	40.937***	31.144***
0.9	0.925	0.836	0.283	10.123***	9.468***	8.430***
			Panel F: MS-LPPLS-CI Factors of the G7 and the BRICS			
0.1	5.200***	4.602***	4.461***	4.316***	8.160***	7.200***
0.2	6.705***	6.960***	4.994***	5.649***	10.134***	9.521***
0.3	7.277***	7.253***	5.307***	6.499***	10.529***	10.900***
0.4	7.946***	6.921***	4.836***	7.405***	9.949***	11.643***
0.5	8.235***	6.453***	4.799***	7.525***	9.296***	11.869***
0.6	7.860***	6.703***	5.418***	7.794***	8.531***	11.617***
0.7	7.439***	6.535***	5.565***	7.358***	8.211***	10.863***
0.8	6.761***	5.653***	5.483***	6.308***	7.679***	9.457***
0.9	4.957***	4.362***	3.701***	4.425***	5.617***	7.032***

Note: The table reports the quantile causality test statistics for causality running from the gold to platinum price ratio (LGP) to the MS-LPPLS-CIs for a particular quantile listed in the first column. Panels A through E report the findings for the bubble indicators for each BRICS economy and Panel F reports the same for the factors derived from the DFM applied to the G7 and BRICS MS-LPPLS-CIs. ***, ** and * indicate rejection of the null hypothesis of no Granger causality at the 1%, 5% and 10% levels of significance respectively (critical values of 2.575, 1.96, 1.645 for the standard normal test statistic).