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Investor sentiment and multi-scale positive and negative stock market bubbles in a panel of G7 countries☆

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A B S T R A C T

Firstly, we use the log-periodic power law singularity multi-scale confidence indicator (LPPLS-CI) approach to detect both positive and negative bubbles in the short-, medium- and long-term stock market indices of the G7 countries. Secondly, we apply heterogeneous coefficients panel data-based regressions to analyse the impact of investor sentiment, proxied by business and consumer confidence indicators, on the indicators of bubbles of the G7. Controlling for the impacts of output growth, inflation, monetary policy, stock market volatility, and growth in trading volumes, we find that investor sentiment increases the positive and reduces the negative LPPLS-CIs, primarily at the medium- and long-term scales for the G7, considered together, with the result being driven by at least five of the seven countries. Our results have important implications for both investors and policymakers, as the collapse (improvement) of investor sentiment can lead to a crash (recovery) in a bull (bear) market.

1. Introduction

Many market participants are emotional and reactionary, and thus tend to make overly optimistic or pessimistic judgments and choices. Following the seminal contributions of Baker and Wurgler (2006, 2007), which underline the importance of investor sentiment for movements in the US stock market, many studies (see for example, Bathia and Bredin (2013), Bathia et al. (2016), Jawadi et al. (2018), Rahman and Shamsuddin (2019), and Lee and Chen (2020)) highlight the driving role of investor sentiment for the stock market returns of the G7 countries (Canada, France, Germany, Italy, Japan, the United Kingdom (UK), and the United States (US)).

While existing studies agree that market sentiment can drive movements in stock market indices, an important associated question would be: how does it impact stock market bubbles? The theoretical models of Barberis et al. (1988) and Daniel et al. (1998) suggest that a reversal of investor sentiment could be associated with the bursting of equity market bubbles. The only available study that tends to lend empirical support to this theoretical proposition is the work of Pan (2020), which examines the relationship between US stock market bubbles and consumer confidence indexes, as proxies for investor sentiment, and indicates that investor sentiment positively and in a statistically significant manner affects the probability of stock bubble occurrences.

In this paper, we extend the work of Pan (2020) to an international context by going beyond the US, and considering the six other advanced equity markets comprising the G7 bloc. Specifically, we analyse the impact of the metrics of business or consumer confidence on the equity market bubbles of these countries using monthly data over the period 1973:02 to 2020:09 in a panel data setting. The choice of the G7 is not only driven by the availability of data, which allows us to cover nearly 5 decades of extreme movements in the stock markets of these developed economies, but also by the fact that the G7 bloc accounts for nearly two-thirds of global net wealth and nearly half of world output, and hence the dynamics of bubbles in these stock markets are likely to have a worldwide spillover effect and impact the sustainability of the global financial system (Das et al., 2019). The decision to rely on panel data regressions is motivated by the high degree of synchronization of the indicators of the bubbles, which we discuss in detail below, with strong evidence of connectedness in terms of investor sentiment (and speculation) within these markets also being reported in the works of Plakandaras et al. (2020), Demirer et al. (2021), and Tiwari et al. (2021). Even

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though we conduct the estimation in a panel setting, we allow for heterogeneous responses of bubbles to investor sentiment (and other controls) by using the random coefficients (RC) approach of Swamy (1970) to derive both overall and country-specific results.

To detect bubbles, 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, we also apply the multi-scale LPPLS confidence indicators (LPPLS-CI) of Demirer et al. (2019) to characterize positive and negative bubbles at different timescales, i.e., short-, medium- and long-term, corresponding to estimation windows associated with trading activities over one to three months, three months to a year, and one year to two years, respectively. Note that the identification of both positive and negative multi-scale bubbles is not possible based on the wide array of other existing statistical tests (see, Balcilar et al. (2016), Zhang et al. (2016), and Sornette et al. (2018, for detailed reviews), which points to the suitability and added value of our applied methodology. We consider this important because it allows us to gauge the possible asymmetric effect of investor sentiment on the equity market bubbles of the G7, given that crash and recovery at different horizons can carry different information for market participants, as suggested by the heterogeneous market hypothesis (HMH) (Müller et al., 1997). It should be pointed out that the study of Pan (2020) only deals with positive bubbles and does not make any distinction across timescales, which makes our analysis more comprehensive because it considers the six advanced equity markets other than the US within the G7 bloc as well as the US equity market. To the best of our knowledge, this is the first paper to analyse the effect of investor sentiment, as captured by business and consumer confidence measures, on six indicators of multi-scale positive and negative bubbles in the G7 countries based on a heterogeneous coefficients panel data model.

Our results show major crashes and booms in the G7 stock markets over the sample period of 1973:02 to 2020:09. The impact of investor sentiment on bubble indicators is asymmetric, increasing the positive and reducing the negative bubbles mainly at the medium- and long-term scales, which points to the importance of the behavioural indicators of investors for the boom and bust cycles in G7 equity markets.

It would be interesting to briefly outline the possible theoretical models used to relate investor sentiment to bubbles (see Scherbina and Schlusche (2014, for a detailed review). The first class of models concerns the differences of opinion and short sale constraints. This class considers a setting with investor disagreement, and shows that, if optimistic investors are boundedly rational, or simply dogmatic about their beliefs, they fail to take into account that other agents in the economy may have more pessimistic views about an asset but cannot sell it due to short sale constraints. The resulting market price of the asset is too high relative to the fair value. The second class of models incorporate feedback trading, which generates bubbles by assuming that a group of traders builds their trading demands solely on past price movements, and hence leads bubbles to grow for a period of time before they eventual collapse. The third theoretical model is based on biased self-attribution. In this model, a representative investor suffers from biased self-attribution, which leads people to take into account 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 investor tendency to be too slow to revise models, such that they under-weigh relevant but non-attention-grabbing (routine) evidence, which leads to under-reaction.

The remainder of the paper is organized as follows: Section 2 discusses the data and the basics of the econometric model. Section 3 presents the empirical findings involving the detection of bubbles, as well as the effects of investor sentiment on the six LPPLS-CIs of bubbles in the panel of G7 countries. Finally, Section 4 concludes.

2. Data and econometric model

2.1. Data

We first obtain weekly bubble indicators, derived from the natural logarithmic values of the daily dividend-price ratio of the seven countries, using the dividend and stock price index series, in their local currencies, obtained from Refinitiv Datastream. Appendix A outlines the mathematical details of how the multi-scale LPPLS-CIs are obtained. The generated bubble indicators cover weekly periods from the 1st week (7th) of January, 1973 to the 2nd week (13th) of September, 2020. Since, our controls, following Pan (2020) and Caraiani et al. (2023), namely the macroeconomic variables trading volume and (realized) volatility, as well as the indicators of investor sentiment, are at monthly frequency, to obtain a monthly value for each multi-scale confidence indicator, we take the average for each weekly value that falls within a given month. For the macroeconomic control variables, we use 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. For the interest rate variable, we use the three-month money market interest rate merged with the shadow short rate (SSR) of the individual countries (of course, from 1999 onwards France, Germany, and Italy have the same values), from the time the latter becomes available. Data on industrial production, CPI, and the money market interest rates are all sourced from the Main Economic Indicators (MEI) database of the Organization for Economic Co-operation and Development (OECD).[1] Specifically, barring the US data, which begins in 1985:11, the SSRs of the countries are available from 1995:01. The SSRs are derived from the website of Dr. Leo Krippner.[2]

To capture volatility, we use the measure of realized volatility of Andersen and Bollerslev (1998), whereby we take the sum of squared daily log-returns over a month. The trading volume is obtained from Refinitiv DataStream, and we take month-on-month growth rates to ensure stationarity.

Finally, our main predictor, investor sentiment, is measured using the OECD standardized seasonally-adjusted survey-based Consumer Confidence Indicator (CCI) and Business Confidence

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

2 https://www.ljkmfa.com/. 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, which are considered an improvement over those obtained by Wu and Xia (2016, for the Euro area, UK, and US), as discussed in detail by Krippner (2020). The SSR is based on models of the term-structure, which essentially remove 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 period, and in turn use it as the common metric of monetary policy stance across the conventional and unconventional monetary policy episodes.

Indicator (BCI),[3] with both being amplitude adjusted and having a long-term average of 100. The BCI and CCI are also obtained from the MEI of the OECD. The BCI provides leading information, based on opinion surveys of developments in production, orders, and stocks of finished goods in the industry sector. Numbers above 100 suggest an increased confidence in near future business performance, and numbers below 100 indicate pessimism towards future performance. The CCI provides a leading indication of households' consumption and savings, based on answers regarding their expected financial situation, sentiment about the general economic situation, unemployment, and the capability of savings. An indicator above 100 signals a boost in consumer confidence about the future economic situation, as a consequence of which they are less prone to save and more inclined to spend money on major purchases in the next 12 months. Values below 100 indicate a pessimistic attitude towards future developments in the economy, possibly resulting in a tendency to save more and consume less.

Ultimately, based on data availability and transformations to ensure stationarity, our panel data-based regression covers monthly data from 1973:02 to 2020:09, and is an unbalanced panel, due to a lack of data on trading volume and investor sentiment indicators for some countries over the entire sample period.

2.2. Econometric framework

To capture the effect of investor sentiment on equity market bubbles at various timescales, we specify the following panel data model:

$$eq\_bubble^{j}_{i,t} = \beta_{0i} + \beta_{1,i} is_{i,t} + \beta_{ki} Z_{i,t} + \varepsilon_{i,t} \tag{1}$$

where $eq\_bubble^{j}_{i,t} = \left\{lt_{neg_{i,t}}, mt_{neg_{i,t}}, st_{neg_{i,t}}, lt_{pos_{i,t}}, mt_{pos_{i,t}}, st_{pos_{i,t}}\right\}$, $j = 1, 2, \ldots, 6$ represents negative and positive equity market bubbles at short-, medium- and long-run timescales, which correspond to estimation windows associated with trading activities over one to three months, three months to a year, and one year to two years, respectively (see, Appendix A for further details); is_{it} is the investor sentiment indicator, which involves either $bci_{i,t}$ or $cci_{i,t}$, capturing business and consumer confidence indicators, respectively; while Z_{it} is a set of control variables, with $Z'_{i,t} = \left\{ip_{growth_{i,t}}, cpi_{growth_{i,t}}, ir_{diff\,i,t}, rv_{it}, tv_{growth_{i,t}}\right\}$, comprising industrial production growth, CPI inflation growth, changes in interest rates, realized volatility, and total volume growth. The β's in Eq. (1) capture the cross-section-specific (country-level) parameters, and the idiosyncratic error term ($\varepsilon_{i,t}$) is distributed with mean zero and variance $\sigma_{ii,t}I$. The model is estimated using the random coefficients (RC) approach, discussed in detail in Appendix B.

3. Empirical findings

We start by discussing each scale of the multi-scale LPPLS-CI values for the G7 countries, then the impact of investor sentiment measures on these indicators based on the panel data regression.

3.1. Identification of bubbles in the G7 countries

In Fig. 1, the short-, medium- and long-term indicators are displayed in 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 is calibrated.

We see four strong positive long-term LPPLS-CI values. The first is observed in Canada, France, Germany, Italy, the UK and US from 1973 to 1974. This strong indicator value precedes one of the worst global market downturns since the Great Depression, lasting from 1973:01 through to 1974:12. This crash comes on the heels of the collapse of the Bretton Woods system, and the dollar devaluation from the Smithsonian Agreement. The second positive long-term LPPLS-CI value is strong, preceding Black Monday in 1987:10 in Canada, Japan, the UK and US. A third positive value is observed for Canada, the UK, US, and, to some extent, Germany, during the Asian financial crisis of 1997. The fourth value is a clustering of highly positive LPPLS-CI values leading up to the dot-com bubble burst from 2000:03 to 2002:10, especially for Canada, France, Italy, the UK and US. Immediately following the crash, we see strong negative LPPLS-CI values, which signal booms in these countries. While there are not as many negative LPPLS-CI values as positive LPPLS-CIs, they are strong and exist for all G7 countries, except the US, following the global financial crisis (GFC), suggesting faster stock market recoveries in the remaining six countries.

In general, for the medium-term we observe pronounced LPPLS-CI values (positive and negative) at points where we detect the same for the long-term indicators. Strong positive medium-term LPPLS-CI values are formed before strong long-term LPPLS-CI values leading up to the GFC. The short-term LPPLS-CIs produce the most signals. It can be inferred from Fig. 1 that the smallest crashes/booms are signalled at this short-term scale, possibly due to it picking up idiosyncratic signals. However, we can still see small corrections immediately following strong short-term LPPLS-CI values. It is interesting to note, just as for the medium-term indicators preceding long-term indicators, that short-term indicators tend to lead medium-term indicators, in the context of the major bubble dates identified by the medium- and long-run indicators. This adds support to the finding of Demirer et al. (2019) that the maturation of a bubble towards instability is present across several distinct timescales.

Note that, besides the crisis episodes discussed, the indicators generally show spikes associated with crashes and recoveries before and around the European sovereign debt crisis of 2009 to 2012, Brexit in 2016, and, to some extent, the COVID-19 outbreak, especially the positive bubble indicator for the US.

We observe similar timings of strong (positive and negative) LPPLS-CI values across the G7, i.e., synchronized boom and bust cycles of the seven developed equity markets, which motivates the use of a panel-based approach to analysing the impact of investor sentiment on stock market bubbles.

3.2. Effect of investor sentiment on bubbles

In this section, the RC (Swamy, 1970) estimation results for Eq. (1) for all countries combined, and the country-specific results of the effect of investor sentiment on equity market bubbles are reported.

We model the contemporaneous impact of investor sentiment on equity market bubbles, as the application of the Hausman (1978) test for endogeneity suggests that business and consumer confidence and control variables are exogenous to the specification, with complete details of these results available upon request from the authors. The impact of *bci* and *cci* on negative equity

[3] Traditionally, in the literature, two approaches are followed to measure the latent investor sentiment (see Zhou (2018, for a detailed discussion). The first relies on various market-based measures (for example, trading volume, closed-end fund discount, initial public offering (IPO) first-day returns, IPO volume, option implied volatilities (VIX), or mutual fund flows) as proxies for investor sentiment. The second comprises survey-based indexes (such as the AAII Investor Sentiment Survey, University of Michigan Consumer Sentiment Index (just as our CCI and BCI), the UBS/GALLUP Index for Investor Optimism, or investment newsletters). We take the second approach (i.e. survey-based indexes) due to the free availability of the data, and being comparable as they are derived from the same source, and follow Pan (2020) in this regard, who concludes that such survey-based indexes are "good proxies for investor sentiment".

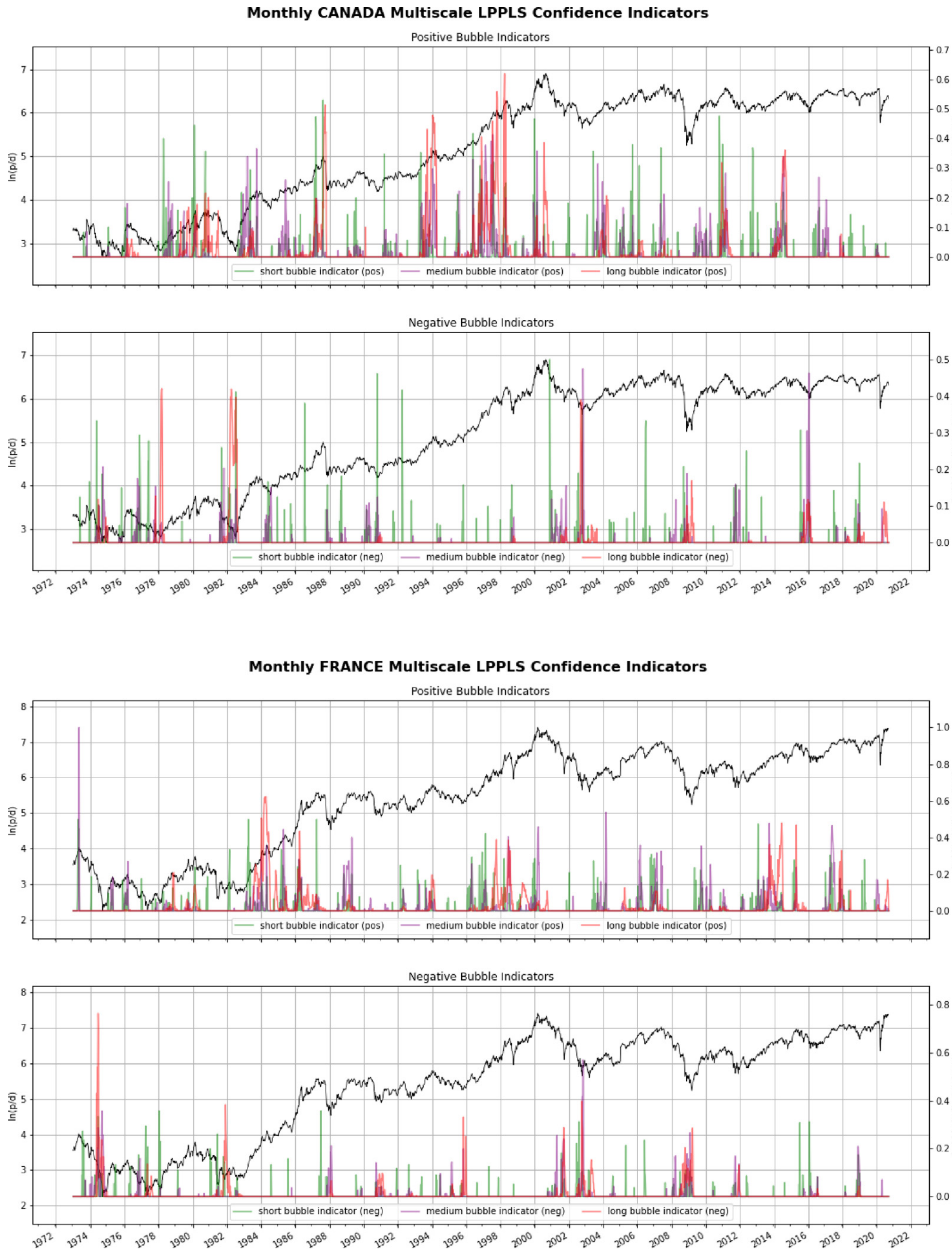

Fig. 1. Monthly Multi-Scale LPPLS-CIs of the G7 Countries.

market bubbles across the three timescales is given in Table 1, while the same for the multi-scale positive bubble indicators is given in Table 2.

From Table 1, it is evident that both *bci* and *cci* exert a negative and statistically significant impact on negative equity market bubbles, primarily in the medium and long term. The impact of *bci* and *cci* on short-term negative equity market bubbles is also negative, but this impact is not statistically significant. Considering the impact of the two investor sentiment indicators on positive equity market bubbles, we note that the impact of both business and consumer sentiment is positive and statistically significant on positive equity market bubbles, but again is restricted to the medium and long term. The impact of *bci* and *cci* on positive equity market bubbles is positive in the short term, but not statistically significant.[4]

Intuitively, these findings make sense, given that a positive bubble indicator signals rapid growth in the stock markets before the crash, while a negative bubble indicator captures the recovery following a decline. Specifically, we find that, higher values

[4] Following a suggestion from an anonymous referee, we estimate fixed and random effects models, only picking up a statistically significant positive impact of sentiment on the medium- and long-term positive bubble indicators. Complete details of these results are available upon request from the authors. They are not reported here because these two estimation methods do not allow us to capture the country-level heterogeneity accounted for by the RC approach (which we discuss in detail below).

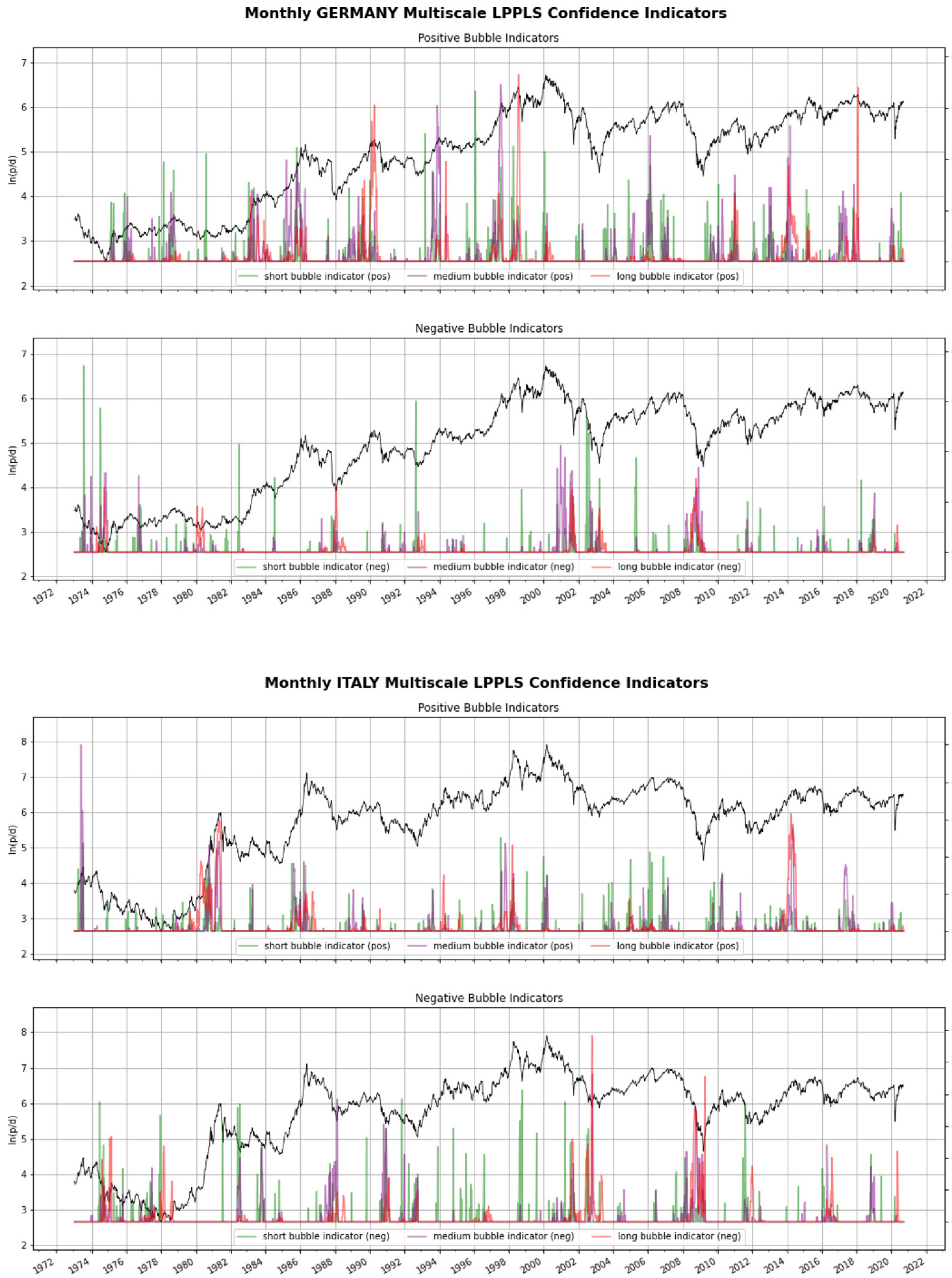

Fig. 1. (*continued*).

of investor sentiment tend to increase the positive LPPLS-CIs, while the same reduces the corresponding negative indicators. This is understandable, as strong investor sentiment causes the market to grow quickly before a crash, and in the same way, rebound quicker when the market is declining.[5] Even though Pan (2020) does not identify negative bubbles, our evidence is in line with the finding that investor sentiment enhances the likelihood of the occurrence of (positive) stock market bubbles. Furthermore, with the long- and medium-term scales based on larger calibration time periods than the short-run LPPLS-CIs, the former two scales tend to be relatively less idiosyncratic, as outlined in the preceding sub-section. With the behavioural variables significantly impacting the long- and medium-term LPPLS-CIs, the evidence suggests that investor sentiment is associated with deeper equity market crashes and recoveries, thus making investor sentiment an important driver of the boom-bust cycles in the G7 equity markets. Interestingly, the *bci* has a stronger impact than the *cci* for the medium-term bubble indicators, at (at least) the 5% level of significance, while the reverse is true for the long-term bubble indicators. With the medium-term LPPLS-CIs leading the long-run indicators, the business-related sentiment becomes

[5] Based on the suggestion of an anonymous referee, we re-conduct the analysis by replacing sentiment with the newspaper-based Economic Policy Uncertainty (EPU) indexes of the G7 countries developed by Baker et al. (2016), available for download from: https://policyuncertainty.com/all_country_data.html. We find that EPU only tends to significantly impact the medium- and long-term positive bubble indicators, with the effect being negative in line with intuition, given the negative association between uncertainty and sentiment (Lee et al., 2021; Lee and Lee, 2023). Complete details of these results are available upon request from the authors.

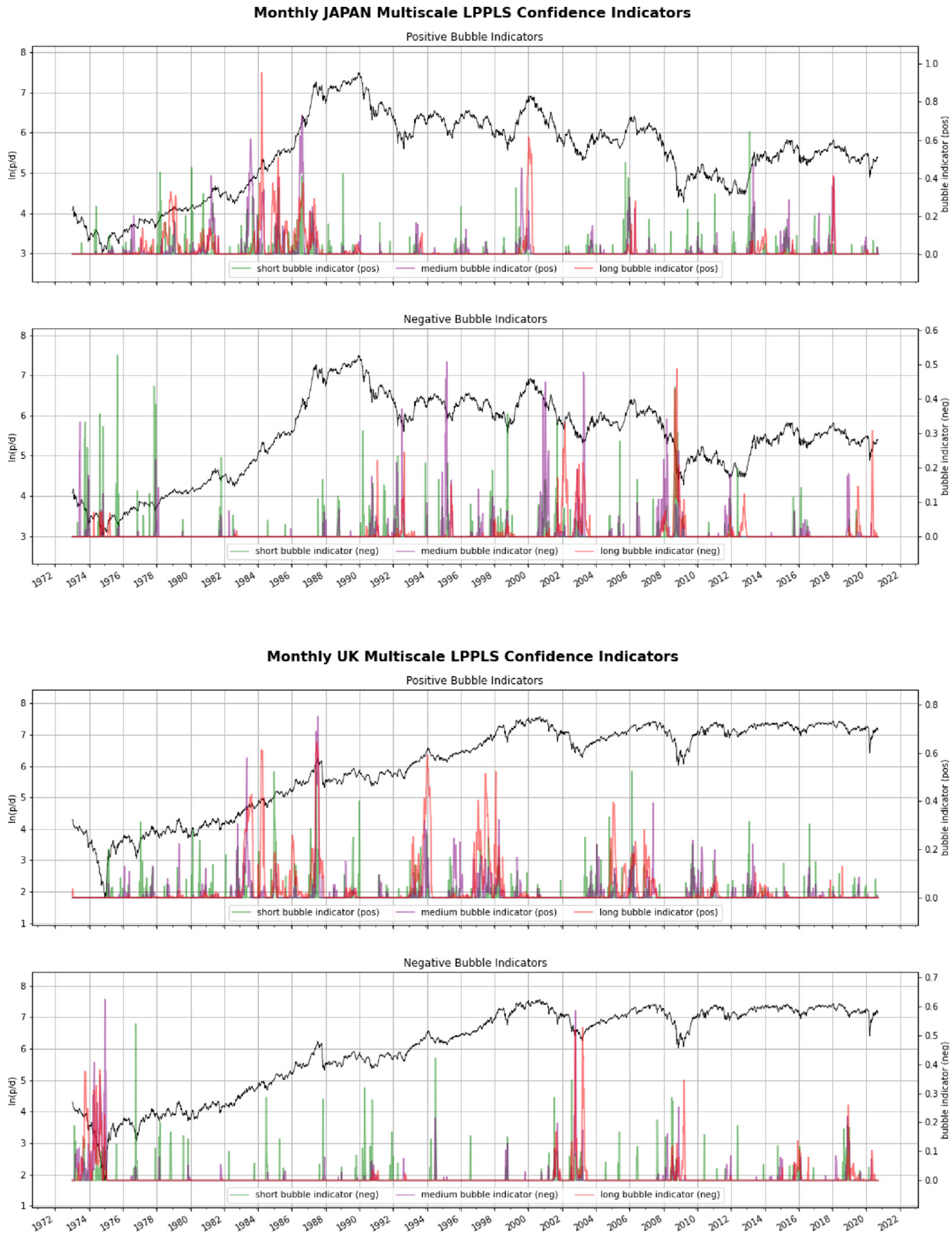

Fig. 1. (*continued*).

comparatively more important, with consumer confidence making these effects stronger in the long term. Finally, in general, the absolute values of the coefficients of the investor sentiment variables reveal a stronger effect on the positive bubble indicators than the negative indicators. This implies that higher investor sentiment can indeed instigate recovery when markets are down, but when markets are booming, the crash effect becomes more powerful.[6]

For the effects of the other controls, besides sporadic impact from output growth, inflation, and interest rate changes, we detect strong associations for realized volatility and growth in trading volume. In line with Pan (2020), particularly realized volatility negatively (positively) impacts the positive (negative) LPPLS-CI indicators, while trading volume growth has the reverse effect on the generation of bubbles.

6 Since the bubble indicators are originally at daily frequency, and a measure of daily global economic sentiment, namely the Societe Generale (SG) Global Sentiment Index (SGGSI) (https://sg-global-sentiment.com/) is available from 11th March 2002, we use the extracted first principal component (PC) of each of the six bubble indicators across the G7, then estimate the ordinary least squares (OLS) regressions relating the six PCs with the SGGSI, detrended linearly to make it stationary. We find that, short- and medium-term PCs of the negative LPPLS-CIs are negatively impacted by the SGGSI in a statistically significant manner (with coefficients −0.277 and −0.350 at the 1% level), and the PCs of the short-term positive indicators are positively driven by SGGSI in a statistically significant fashion (with a coefficient of 2.065 at the 1% level). In essence, investor sentiment positively impacts positive bubbles and reduces negative bubbles. Further details are available upon request from the authors.

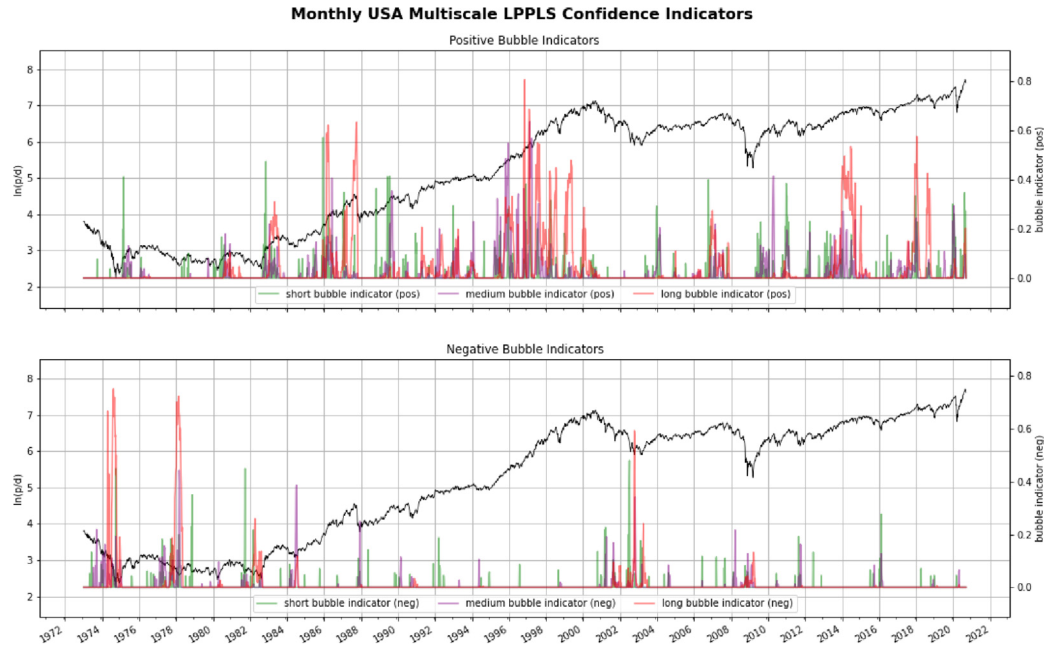

Fig. 1. (*continued*).

Table 1
RC estimation results for negative equity bubbles: 1973:02 to 2020:09.

	(1) lt_{neg}	(2) mt_{neg}	(3) st_{neg}	(4) lt_{neg}	(5) mt_{neg}	(6) st_{neg}
bci	−0.00215*	−0.000600**	0.000207			
	(−1.69)	(−1.98)	(0.74)			
cci				−0.00344**	−0.00115*	−0.000325
				(−2.20)	(−1.76)	(−1.10)
ip_{growth}	−0.174	−0.104	0.0774**	−0.123	−0.131	0.0817***
	(−1.30)	(−1.09)	(2.36)	(−1.12)	(−1.64)	(2.74)
cpi_{growth}	−0.457	−0.315	0.115	−0.734**	−0.329	0.161
	(−1.36)	(−0.69)	(0.57)	(−2.31)	(−0.82)	(0.90)
ir_{diff}	−0.000430	−0.00517	−0.00200	0.000655	−0.00287	−0.00125
	(−0.31)	(−1.07)	(−1.30)	(0.38)	(−0.84)	(−0.96)
rv	1.759***	1.694***	0.829***	1.756**	1.672***	0.785***
	(2.68)	(3.42)	(3.71)	(2.48)	(3.30)	(3.54)
tv_{growth}	−0.00395	−0.0190**	0.00477	−0.00145	−0.0158**	0.00821**
	(−0.67)	(−2.52)	(1.29)	(−0.30)	(−2.21)	(2.04)
constant	0.218*	0.0624**	−0.0180	0.346**	0.117*	0.0355
	(1.70)	(2.06)	(−0.65)	(2.21)	(1.78)	(1.23)
#observations	1720	1720	1720	1873	1873	1873
# groups	7	7	7	7	7	7
Test for par constancy χ^2	400.22	174.52	75.96	452.64	193.74	81.03
d.o.f	42	42	42	42	42	42
Prob.	0.0000	0.000	0.0010	0.0000	0.0000	0.0003

Note:Business confidence indicator (*bci*); consumer confidence indicator (*cci*); industrial production growth (ip_{growth}); consumer price index growth (cpi_{growth}); interest rate difference (ir_{diff}); realized volatility (*rv*); total volume growth (tv_{growth}); long-term negative bubble (lt_{neg}); medium-term negative bubble (mt_{neg}); short-term negative bubble (st_{neg}); *t*-statistics (based on bootstrapped robust standard errors) in parentheses.
*p<0.10.
**p<0.05.
***p<0.01.

We next turn to the country-specific results for the sample of the G7 economies in order to understand the drivers of the overall results. Table 3 presents the results for the impact of *bci* and *cci* on negative equity market bubbles at the short-, medium-, and long-term scales, while Table 4 reports the results of the impact of the two alternative metrics of investor sentiment on the positive equity market bubble indicators across the three timescales.

For the negative LPPLS-CIs, we observe negative and significant effects from the *bci* for France, and Japan at the long-term scale; Italy at both the medium- and long-term scales; and the US

Table 2
RC estimation results for positive equity bubbles: 1973:02 to 2020:09.

	(1) lt_{pos}	(2) mt_{pos}	(3) st_{pos}	(4) lt_{pos}	(5) mt_{pos}	(6) st_{pos}
bci	0.0132*	0.00281***	0.000163			
	(1.79)	(3.49)	(0.26)			
cci				0.00369**	0.00152*	−0.000310
				(2.16)	(1.89)	(−0.30)
ip_{growth}	−0.0799	0.0533	0.0394	0.452	0.153	0.0741
	(−0.59)	(0.87)	(0.51)	(1.06)	(1.14)	(0.65)
cpi_{growth}	−1.293	0.216	1.070	−1.583	0.00218	0.929
	(−1.08)	(0.21)	(1.15)	(−1.01)	(0.00)	(0.98)
ir_{diff}	0.00816	0.0153**	0.00216	0.0142	0.0150**	0.000248
	(1.20)	(2.13)	(0.49)	(1.49)	(2.09)	(0.06)
rv	−0.0954	−0.339**	−0.650***	−0.125	−0.386**	−0.642***
	(−0.38)	(−2.24)	(−4.10)	(−0.65)	(−2.30)	(−4.91)
tv_{growth}	−0.00185	0.00525	0.0194**	−0.00308	0.00129	0.0190**
	(−0.25)	(0.99)	(2.47)	(−0.35)	(0.24)	(2.55)
constant	−1.297*	−0.264***	−0.00176	−0.343**	−0.134*	0.0461
	(−1.77)	(−3.28)	(−0.03)	(−1.98)	(−1.65)	(0.44)
# observations	1720	1720	1720	1873	1873	1873
# groups	7	7	7	7	7	7
Test for par constancy χ^2	109.59	51.95	50.57	122.03	59.65	62.30
d.o.f	42	42	42	42	42	42
Prob.	0.0000	0.1397	0.1711	0.0000	0.0377	0.0225

Note: Business confidence indicator (*bci*); consumer confidence indicator (*cci*); industrial production growth (ip_{growth}); consumer price index growth (cpi_{growth}); interest rate difference (ir_{diff}); realized volatility (*rv*); total volume growth (tv_{growth}); long-term positive bubble (lt_{pos}); medium-term positive bubble (mt_{pos}); short-term positive bubble (st_{pos}); *t*-statistics (based on bootstrapped robust standard errors) in parentheses.
*$p<0.10$.
**$p<0.05$.
***$p<0.01$.

Table 3
RC estimation results: Country-specific impact of sentiment on negative equity market bubbles: 1973:02 to 2020:09.

	Investor Sentiment	lt_{neg}	mt_{neg}	st_{neg}
Canada	*bci*	−0.00164 (−1.39)	−0.00037 (−0.57)	0.00079 (1.27)
	cci	−0.00068 (−0.74)	−0.00138 (−1.49)	−0.00052 (−1.05)
France	*bci*	−0.00276** (−2.31)	−0.00041 (−0.65)	−0.00029 (−0.58)
	cci	−0.00708*** (−3.71)	−0.00042 (−0.37)	−0.00100* (−1.89)
Germany	*bci*	−0.00135 (−1.15)	0.00053 (0.84)	0.00053 (0.82)
	cci	−0.00360*** (−3.02)	−0.00234** (−2.28)	−0.00018 (−0.33)
Italy	*bci*	−0.00346** (−2.34)	−0.00141** (−2.45)	0.00051 (0.83)
	cci	−0.00011 (−0.09)	0.00111 (1.25)	0.00100 (2.07)
Japan	*bci*	−0.00807*** (4.37)	−0.00089 (−1.34)	0.00044 (0.69)
	cci	−0.01074*** (−6.74)	−0.00273** (−2.33)	−0.00103** (−2.00)
UK	*bci*	0.00259** (2.24)	−0.00040 (−0.72)	0.00027 (0.55)
	cci	−0.00193* (−1.79)	0.00030 (0.47)	−0.00023 (−0.53)
US	*bci*	−0.00004 (−0.71)	−0.00134** (−2.43)	−0.00062 (−0.98)
	cci	−0.00007** (−2.23)	−0.00228*** (−3.16)	−0.00035 (−0.79)

Note: Business confidence indicator (*bci*); consumer confidence indicator (*cci*); long-term negative bubble (lt_{neg}); medium-term negative bubble (mt_{neg}); short-term negative bubble (st_{neg}); *t*-statistics (based on bootstrapped robust standard errors) in parentheses.
*$p<0.10$.
**$p<0.05$.
***$p<0.01$.

at the medium-term scale. Interestingly, the UK shows a counter-intuitive positive impact from *bci* in the long term. For *cci* under negative bubbles, the main impact is from France, Germany, Japan, the UK and US, with, respectively, effects at the long- and short-term, long- and medium-term, all three timescales, long-term, and long-and medium-term. In other words, in line with the overall results, the most significant impact of *bci* and *cci* is observed for the long- and medium-term scales, though some effects are also observed at the short term for the latter for France and Japan. In summary, 5 countries (excluding Canada, and Germany or Italy) of the G7 bloc are affected by *bci* and *cci*, respectively.

For the positive LPPLS-CIs, *bci* impacts the long-term scale only of Canada and Germany, but both medium- and long-term indicators of France, Japan, the UK and US. For *cci*, a significant effect is found for Canada at the long-term scale only, medium-

Table 4
RC estimation results: Country-specific impact of sentiment on positive equity market bubbles: 1973:02 to 2020:09.

	Investor Sentiment	lt_{pos}	mt_{pos}	st_{pos}
Canada	*bci*	0.00640***	0.00042	0.00127
		(2.71)	(0.30)	(1.19)
	cci	0.00454*	0.00037	0.00128
		(1.67)	(0.32)	(0.97)
France	*bci*	0.00463**	0.00300*	−0.00062
		(2.22)	(1.91)	(−0.65)
	cci	0.00600**	0.00156	−0.00432***
		(2.14)	(1.23)	(−2.81)
Germany	*bci*	0.00774***	0.00184	−0.00077
		(2.98)	(1.12)	(−0.72)
	cci	0.00934***	0.00220*	−0.00177
		(4.16)	(1.68)	(−1.34)
Italy	*bci*	0.00237	0.00383***	0.00096
		(0.93)	(2.66)	(1.09)
	cci	−0.00191	−0.00084	0.00080
		(−0.99)	(−0.74)	(0.78)
Japan	*bci*	0.00513***	0.00262*	−0.00149
		(2.62)	(1.79)	(−1.40)
	cci	0.00320**	0.00374***	0.00250**
		(2.14)	(3.16)	(1.97)
UK	*bci*	0.00700***	0.00295**	0.00070
		(2.87)	(2.22)	(0.91)
	cci	0.00560**	0.00196*	0.00036
		(2.55)	(1.72)	(0.45)
US	*bci*	0.05665***	0.00489***	0.00101
		(5.29)	(2.92)	(0.94)
	cci	0.00047	0.00175	−0.00071
		(0.15)	(1.41)	(−0.42)

Note: Business confidence indicator (*bci*); consumer confidence indicator (*cci*); long-term positive bubble (lt_{pos}); medium-term positive bubble (mt_{pos}); short-term positive bubble (st_{pos}); *t*-statistics (based on bootstrapped robust standard errors) in parentheses.
*$p<0.10$.
**$p<0.05$.
***$p<0.01$.

and long-term for Germany and the UK, and all scales for Japan (just as for the negative bubble indicator). For France, a positive and significant effect from the *cci* is found at the long-term scale, but a contradictory negative impact is detected in the short term. As with negative bubbles, *bci* and *cci* tend to affect the medium- and long-term scales, shaping the overall impact of the G7 countries for positive bubbles. Overall, *bci* drives positive bubbles in 6 (excluding Italy) countries of the G7, while *cci* does so in 5 (excluding Italy and the US).

To compare our findings for the US to those of Pan (2020), we find that consumer confidence has a significantly negative impact on long- and medium-term negative equity market bubbles, but no impact is detected for positive bubbles from the *cci*. However, business confidence has a pronounced positive impact on long- and medium-term positive equity market bubbles, a finding we cannot compare to Pan (2020), as the author only concentrates on alternative measures of *cci*. Despite this discussion, it is worth noting that a one-to-one correspondence between our findings and those of Pan (2020) is not possible due to the different methods of detecting bubbles, the sample period, the underlying data, and the model employed.[7]

In general, the majority of country-specific results, albeit with some degree of heterogeneity, tend to confirm the overall findings that investor sentiment drives the medium- and long-term scales of the LPPLS-CIs, with relatively stronger (absolute) effects for positive bubbles than negative bubbles.

4. Conclusion

The primary objective of our paper is to analyse the impact of investor sentiment, as captured by business and consumer confidence indicators, on equity market bubbles of the G7 countries. In the first step, we detect positive and negative bubbles in the short-, medium-and long-run for the G7 equity markets using the multi-scale confidence indicator approach. Our findings reveal major crashes and booms in the seven stock markets using monthly data over the period 1973:02 to 2020:09. We also observe similar timings of strong (positive and negative) LPPLS indicator values across the G7 countries, suggesting commonality in the boom-bust cycles of these equity markets. In other words, diversification of investor portfolios across advanced equity markets is not a possibility for market agents across investment horizons during booms or crashes. In the second step,

[7] With a measure of daily economic sentiment available for the US dating back to 1st January of 1980, as developed by Shapiro et al. (2020), we run OLS regressions to capture the effect of this metric of economic sentiment on the corresponding six daily LPPLS-CIs (of the US). We find that, the medium- and long-term negative indicators are statistically significantly affected in a negative manner (with coefficients of −0.020 and −0.008 at the 1% level), while the medium-term positive LPPLS-CIs are affected positively in a statistically significant way (with a coefficient of 0.002 at the 1% level). However, the long-term indicator is found to be negatively affected, with the coefficient (−0.013) being significant at the 1% level. For the PCs (see Footnote 6), this sentiment indicator negatively impacts the PCs of the medium- and long-term negative LPPLS-CIs (with coefficients of −2.182 and −0.876), with the effect being statistically significant at the 1% level, while the corresponding effects on the PCs of the short-, medium- and long-term positive LPPLS-CIs are positive (0.415), positive (0.249), and negative (−1.135), with statistical significance at the 1%, 5%, and 1% levels, respectively. In general, the relationship between investor sentiment and positive bubbles is positive, while it is negatively related to negative bubbles. Further details of these results are available upon request from the authors.

due to of the evidence of synchronicity detected in the bubble indicators across the G7, we use a panel data-based regression, characterized by heterogeneous response to investor sentiment, to study the overall and country-specific impact of business and consumer confidence indicators. Controlling for the impacts of output growth, inflation, monetary policy, stock market volatility, and growth in trading volumes, we find that the behavioural variables increase the positive and reduce the negative LPPLS-CIs, primarily at the medium- and long-term scales, for the G7 countries considered together. Notably, the significant effect on relatively longer timescales is important, as the medium- and long-run LPPLS-CIs are observed to be highly reliable for detecting severe crashes and strong recoveries in the stock markets. At the country level, while there is some minor degree of heterogeneity, we find that, barring Canada under negative bubbles, at least one metric of sentiment, associated with businesses or consumers, strongly predicts crashes and/or recoveries in all cases considered.

With investor sentiment showing strong positive effects on positive bubbles, compared to other traditional macroeconomic and financial indicators, it is recommended that investors and policymakers be careful when the level of investor sentiment tends to peak when the stock markets are booming, because this could imply an imminent market crash. At the same time, when stock prices are declining, higher investor sentiment can help revive the market quickly. Accordingly, policymakers should implement policies that keep investor sentiment in check during bullish regimes of the G7 equity markets, but boost investor sentiment when a bearish phase is underway. With contractionary and expansionary monetary policies known to impact stock markets and investor sentiment in similar ways (Çepni and Gupta, 2021; Çepni et al., 2021), the role of the state-contingent interest rate decisions of the central banks becomes of paramount importance. Having said this, in spite of the high degree of similar movements in the bubble indicators, due to the underlying heterogeneous impact of investor sentiment, policy authorities should design country-specific monetary policy responses. Academically, our results imply a violation of the efficient market hypothesis, with booms and busts in stock markets being driven by behavioural decisions.

As part of future research, it would be interesting to extend our analysis to emerging markets, which are important for the global financial system (Lee et al., 2022). However, this would be contingent on the availability of consistent data on investor sentiment. In addition, the sentiment of monetary policy committees about the state of the macroeconomy and the financial system can also be investigated as a potential determinant of stock market bubbles, given the recent evidence provided by Gardner et al. (2022), which suggests that the sentiment conveyed by the Federal Open Market Committee (FOMC) statements has a significant effect on the US stock market.[8] Finally, while we do identify bubbles in a time-varying fashion, a limitation of our study is that we rely on a constant parameter model, which can be extended in the future to a time-varying setup, by conducting a rolling-window estimation of the framework to see how the effect of sentiment on the bubble indicators evolves over time.

[8] In fact, using the event-based FOMC sentiment data of this study starting in 2000:02 (and available for meeting dates), OLS estimation suggests that perceptions about inflation, output and the labour market have a positive and significant effect (with coefficients of 0.063, 0.188, and 0.111 at the 10%, 10%, and 1% levels, respectively) on the positive long-term LPPLS-CIs of the US, while, the latter two negatively impact the negative medium-term LPPLS-CIs in a statistically significant fashion (with coefficients of −0.019 and −0.016 at the 5% level in both cases). Interestingly, FOMC sentiment about monetary and financial conditions is not found to have a significant impact. Further details of these results are available upon request from the authors.

CRediT authorship contribution statement

Reneé van Eyden: Formal analysis, Methodology, Writing – original draft, Writing – review & editing. **Rangan Gupta:** Project administration, Data curation, Writing – original draft, Writing – review & editing. **Joshua Nielsen:** Formal analysis, Investigation, Methodology, Writing – original draft. **Elie Bouri:** Data curation, Writing – original draft, Writing – review & editing.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix A. Estimating the multi-scale log-periodic power law singularity (lppls) model

To define the LPPLS model, we use the stable and robust calibration scheme developed by Filimonov and Sornette (2013):

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

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

Following Filimonov and Sornette (2013), Eq. (A.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 is written as:

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

where

$$f = \left(t_c - t\right)^m$$
$$g = \left(t_c - t\right)^m \cos[\omega \ln(t_C - t)]$$
$$h = \left(t_c - t\right)^m \sin[\omega \ln\left(t_c - t\right)]$$

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

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

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

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

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

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

which can be done analytically by solving the matrix equation:

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

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

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

We use the sequential least squares programming (SLSQP) search algorithm (Kraft, 1988) to find the best estimation of the three nonlinear parameters $\{t_c, m, \omega\}$.

The LPPLS confidence indicator, introduced by Sornette et al. (2015), 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 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 timescales 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.

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

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

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

Appendix B. Random coefficients (RC) estimation

Fixed- and random-effects models incorporate panel-specific heterogeneity by including a set of nuisance parameters that provide each panel with its own constant term. However, all panels share common slope parameters, which is undesirable in the current context. RC models (Swamy, 1970) are more general, allowing each panel to have its vector of slopes randomly drawn from a distribution common to all panels. The implementation of the estimator ensures the best unbiased linear predictors of the panel-specific draws from said distribution (Poi, 2003).

Consider a general random-coefficients model, with y being the dependent variable and X being the predictor, of the form:

$$y_i = X_i \beta_i + \varepsilon_i \tag{B.1}$$

In the case of RC, each panel specific β_i is related to an underlying common parameter vector β:

$$\beta_i = \beta + v_i \tag{B.2}$$

where $E\{v_i\} = 0, E\{v_i v_i'\} = \Sigma, E\{v_i v_j'\} = 0$ for $j \neq i$, and $E\{v_i \epsilon_j'\} = 0$ for all i and j. We combine Eq. (B.1) and (B.2) to get:

$$\begin{aligned} y_i &= X_i(\beta + v_i) + \varepsilon_i \\ &= X_i\beta + u_i \end{aligned}$$

with $u_i \equiv X_i v_i + \varepsilon_i$. Furthermore:

$$\begin{aligned} E\{u_i u_i'\} &= E\{(X_i v_i + \varepsilon_i)(X_i v_i + \varepsilon_i)'\} \\ &= X_i \Sigma X_i' + \sigma_{ii} I \\ &\equiv \Pi_i \end{aligned}$$

We can stack the P panels:

$$y = X\beta + u \tag{B.3}$$

where:

$$\Pi \equiv E\{u_i u_i'\} = \begin{bmatrix} \Pi_1 & 0 & \cdots & 0 \\ 0 & \Pi_2 & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \cdots & \Pi_P \end{bmatrix}$$

Estimating the parameters in Eq. (B.2) is a standard problem, which can be solved with generalized least squares (GLS):

$$\begin{aligned} \hat{\beta} &= \left(X'\Pi^{-1}X\right)^{-1} X'\Pi^{-1}y \\ &= \left(\sum_i X_i'\Pi_i^{-1}X_i\right)^{-1} \sum_i X_i'\Pi_i^{-1}y_i \\ &= \sum_i W_i b_i \end{aligned} \tag{B.4}$$

where W_i is the GLS weight, and $b_i = (X_i'X_i)^{-1}X_i'y$. The resulting $\hat{\beta}$ for the overall (national) result is therefore a weighted average of the state-specific OLS estimates. For more details on GLS weight and $\hat{\beta}$ variance specification, the reader can refer to Poi (2003).

To obtain the state-specific $\widehat{\beta_i}$ vectors, Judge et al. (1985) suggest restricting attention to the class of estimators $\{\beta_i^*\}$ for which $E\{\beta_i^* | \beta_i\} = \beta_i$, then the state-specific OLS estimator b_i is appropriate. Following Greene's (1997) suggested method of obtaining the variance of $\widehat{\beta_i}$, it follows that $\hat{\beta}$ is both consistent and efficient; and although inefficient, b_i is also a consistent estimator of β.

Poi (2003) suggests a test to determine whether the panel-specific β_is are significantly different from one another. The null hypothesis is stated as:

$$H_0: \beta_1 = \beta_2 = \cdots = \beta_P \tag{B.5}$$

and the test statistic is defined as:

$$T \equiv \sum_{t=1}^{P} \left(b_i - \beta^{\dagger}\right)' \left\{\hat{\sigma}_{ii}^{-1}(X_i X_i)\right\} \left(b_i - \beta^{\dagger}\right) \tag{B.6}$$

where $\beta^{\dagger} = \left\{\sum_{t=1}^{P} \hat{\sigma}_{ii}^{-1} (X_i X_i)\right\}^{-1} \sum_{t=1}^{P} \hat{\sigma}_{ii}^{-1} (X_i X_i)\, b_i$.

The test statistic T is distributed as χ^2 with $k\,(P-1)$ degrees of freedom.

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