

The FCO Cockpit Global Bubble Status Report

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The Financial Crisis Observatory (FCO) monthly report discusses the historical evolution of bubbles in and between different asset classes and geographies.

It is the result of an extensive analysis done on the historical time series of about 450 systemic assets and about 850 single stocks. The systemic assets are bond, equity and commodity indices, as well as a selection of currency pairs. The single stocks are mainly US and European equities. The data is from Thomson Reuters.

In the first part of this report, we present the state of the world, based on the analysis of the systemic assets. In the second part, we zoom in on the bubble behavior of single stocks and discuss some specific cases.

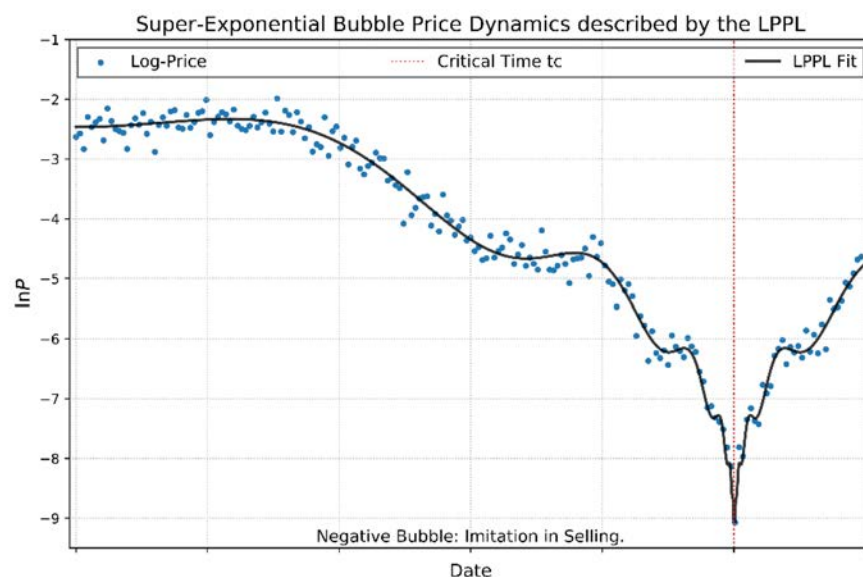
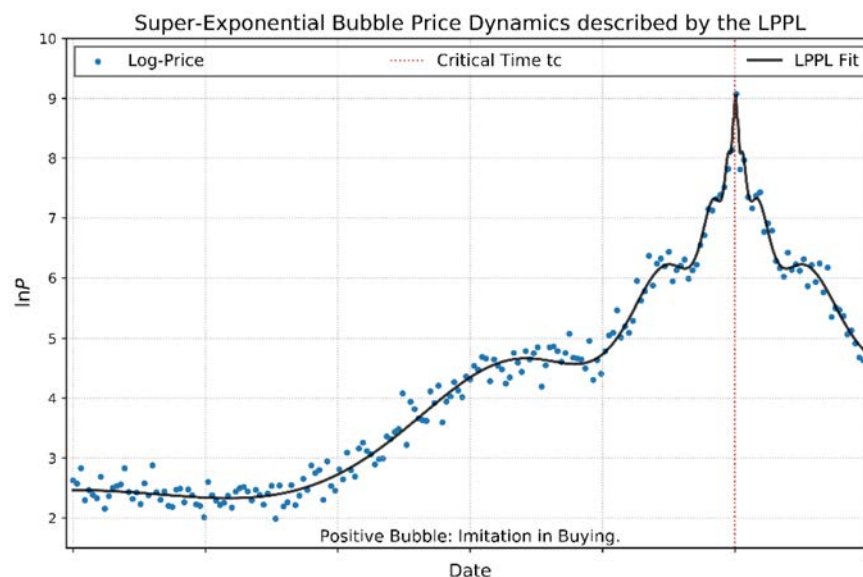
To new readers, we recommend proceeding to the appendix for more detailed information about the methodology and procedures applied in this report.

For an intuitive explanation of the methodology and the specifics of the indicators that are used in this report, we refer to: D. Sornette and P. Cauwels, Financial bubbles: mechanisms and diagnostics. Review of Behavioral Economics 2 (3), 279- 305 (2015)
<http://arxiv.org/abs/1404.2140> and <http://ssrn.com/abstract=2423790>

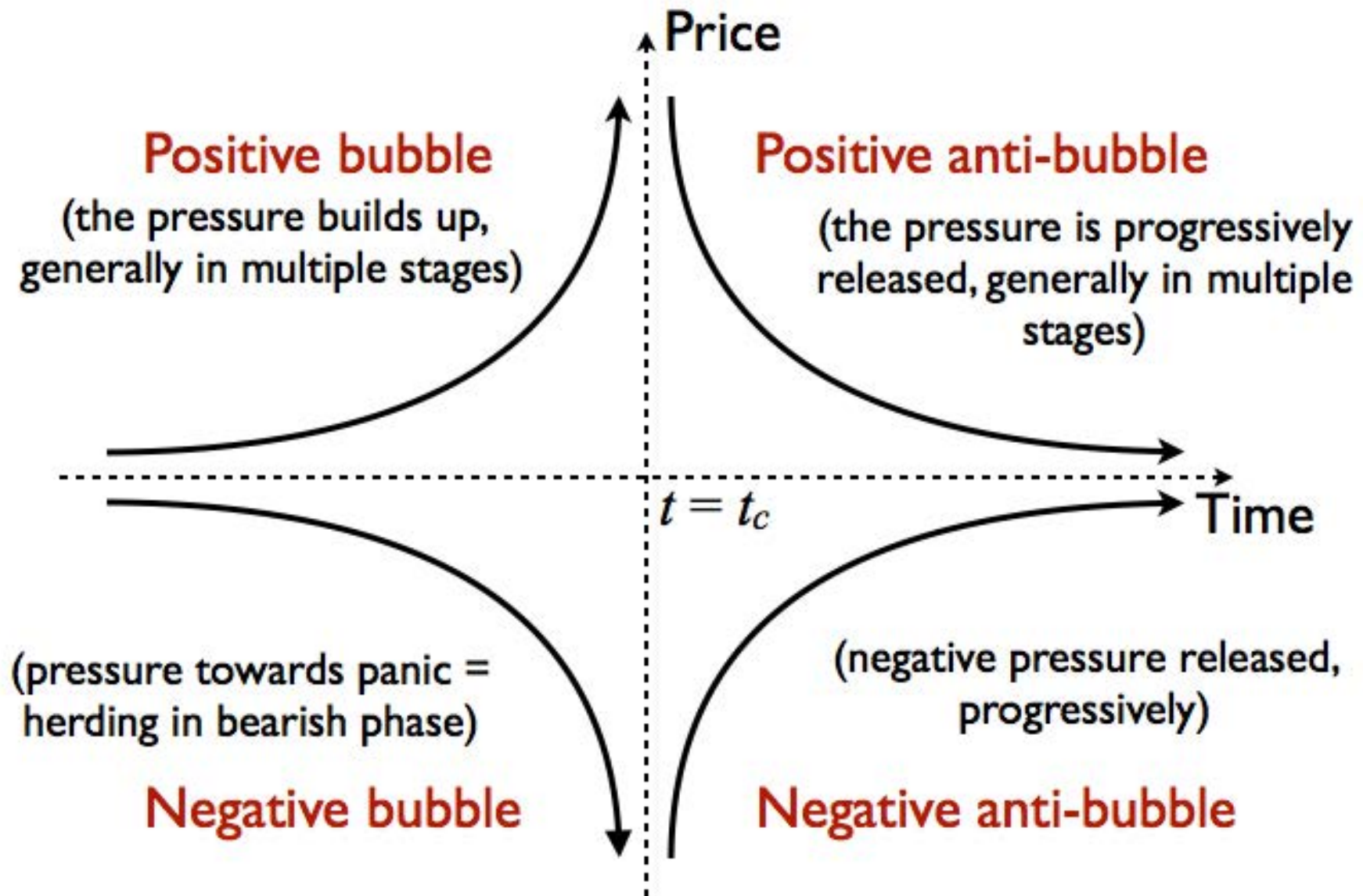
We use the Log-Periodic Power Law Singularity (LPPLS) model to hunt for the distinct fingerprint of **Financial Bubbles**. Basic assumptions of the model are:

1. During the growth phase of a positive (negative) bubble, the price rises (falls) **faster than exponentially**. Therefore the logarithm of the price rises faster than linearly.
2. There are accelerating **log-periodic oscillations** around the super-exponential price evolution that symbolize increases in volatility towards the end of the bubble.
3. At the end of the bubble, the so-called critical time t_c , a finite time singularity occurs after which the bubble bursts.

Together, these effects encompass irrational imitation and herding phenomena amongst market participants that lead to blow-up and instability of asset prices.

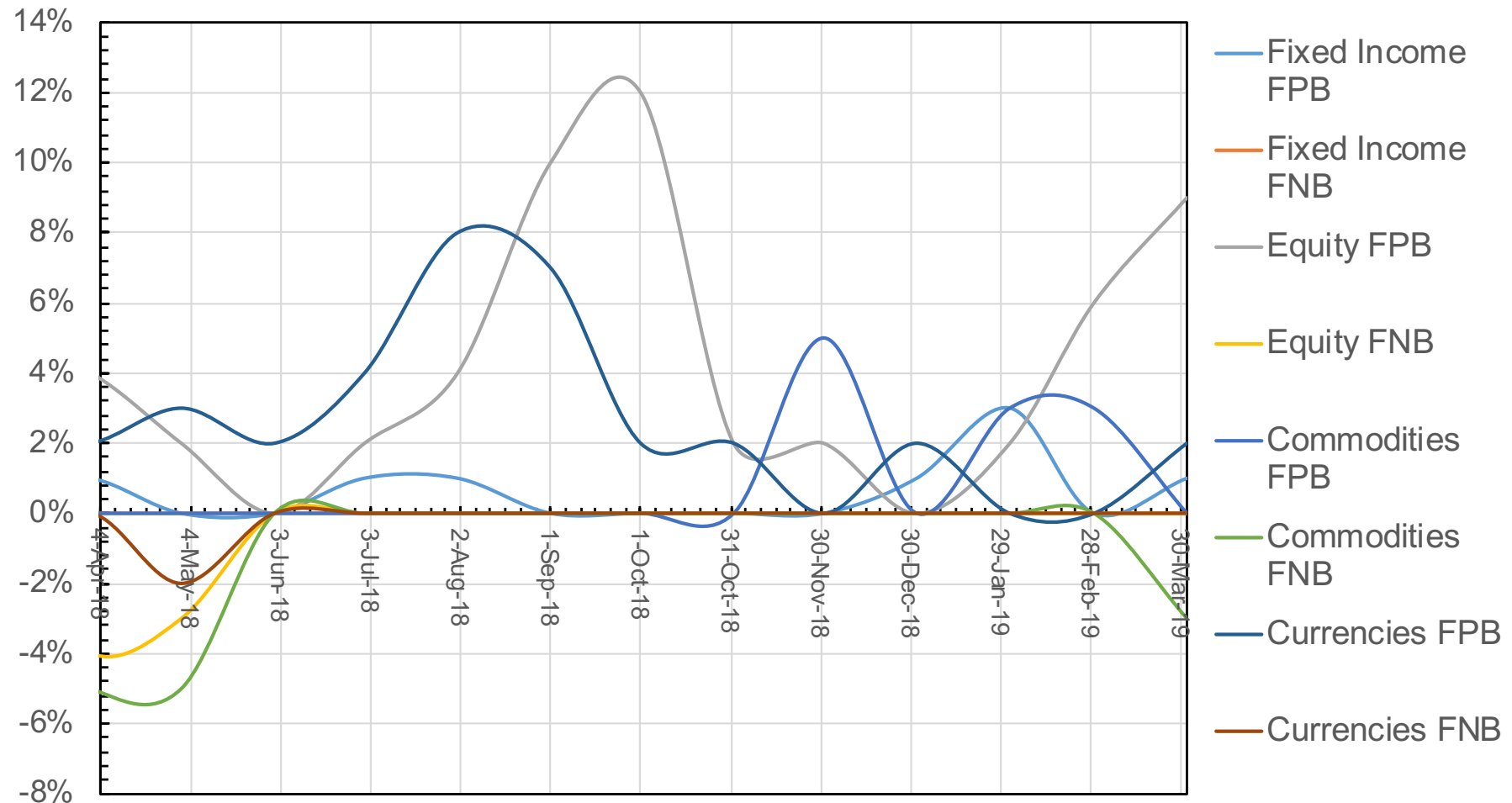


Bubble Regimes



General Results – The Big Picture

Historical evolution of the fraction of assets within an asset class that show significant bubble signals



FPB – Fraction of Positive Bubbles, FNB – Fraction of Negative Bubbles

General Results – This Month's Overview

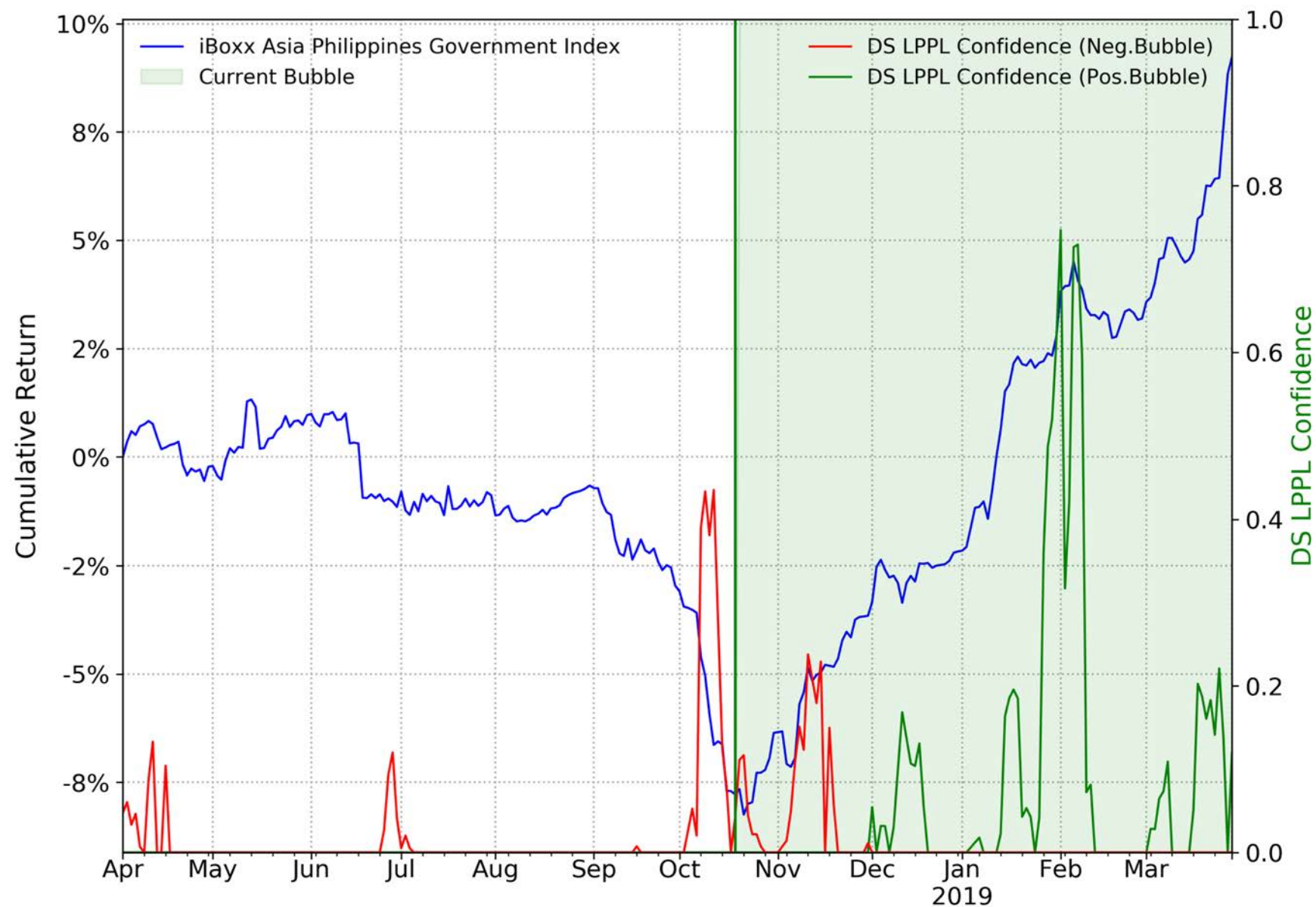
Category	Analyzed Assets	Fraction of Pos. Bubbles [%]	Fraction of Neg. Bubbles [%]
Fixed Income	155	1	0
Government Bonds	55	4	0
Finance and Insurance	21	0	0
Corporate Bonds	79	0	0
Equity	282	9	0
Country Indices	67	4	0
Europe	34	12	0
United States	181	10	0
Commodities	35	0	3
Forex	53	2	0

At the beginning of April, we measure an increase in the fraction of positive bubbles (FPB) for the fixed income, equity and forex asset classes. With 9%, the FPB of equities increases to its highest level since October 2018. For the commodities asset class, the positive bubble signals have decreased back to zero while negative bubble activity has slightly risen. Furthermore, for the first time since the big cryptocurrency market crash following December 2017, we report an increase in positive and negative bubble activity in the sector.

Fixed Income – Government Bond Indices

Bubble Data					Cluster Analysis				
ID	Name	Bubble Size bs [%]	Duration [$days$]	DS LPPL Confidence ci [%]	Geometric Average $\sqrt{bs \cdot ci}$ [%]	Critical Time Prediction		Scenario Probability [%]	
						μ_{tc}	σ_{tc} [$days$]		
Positive Bubbles									
1	iBoxx Asia Philippines Index	18	162	16		17	2019-07-21	27	58

The Fixed Income government bond index analysis reveals positive bubble activity in the Philippine bond market. In the following page, where the evolution of the index and the corresponding DS LPPLS Confidence indicator series are depicted, we see that the index has strongly appreciated since it reached a trough in October - November 2018, that we correctly identified as a negative bubble peak. By now, the reached bubble size amounts to 18% over a duration of approximately 5-6 months, which is a relatively strong increase considering that the index represents (sometimes termed “riskless”) government bonds. The current indicator level is still low, at 16%, which indicates that the strength of the super-exponential growth in the analyzed time series is not yet very pronounced, however there is rising risk requiring to continue monitoring the index in the future.



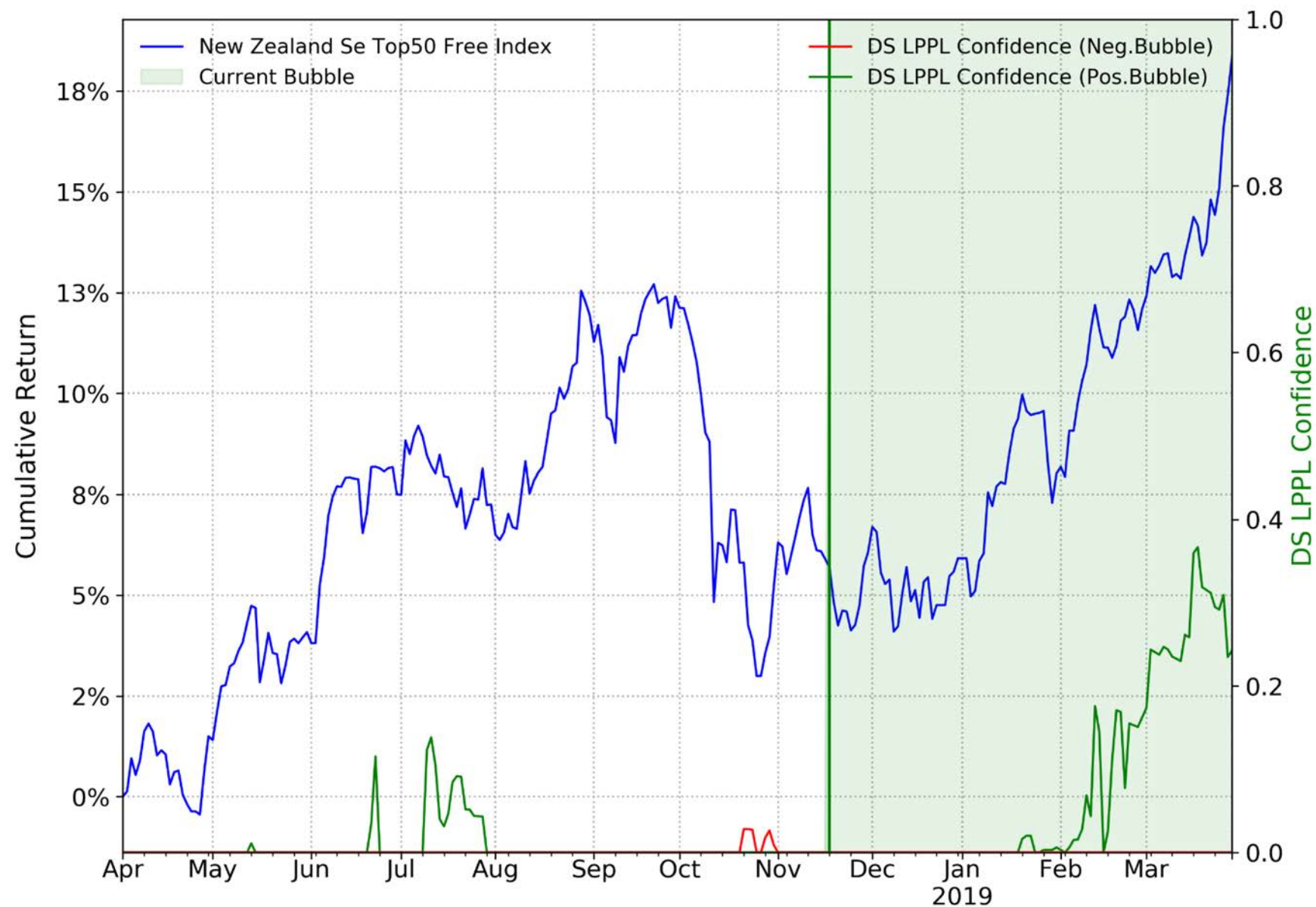
Equities – Country Indices

Bubble Data					Cluster Analysis			
	Name	Bubble Size bs [%]	Duration $[days]$	DS LPPL Confidence ci [%]	Geometric Average $\sqrt{bs \cdot ci}$ [%]	Critical Time Prediction μ_{tc}	σ_{tc} $[days]$	Scenario Probability [%]
Positive Bubbles								
1	FTSE Italia All-Share Index	14	113	63	29	2019-04-19	3	55
2	FTSE MIB Index	14	113	59	29	2019-04-23	3	61
3	New Zealand Se Top50 Free Index	12	132	29	19	2019-04-03	3	83

Amongst the analyzed country equity indices, there are two Italian indices at the top of our list this month. As depicted on the next slide, the market recovery from a long drop in 2018 that could be observed for many different assets since the beginning of 2019, actually led to strong growth which is interpreted as a sign of positive bubble activity by our algorithm. The confidence level is fairly high with around 60% for both indices, while the bubble size is still at an intermediate size. The cluster analysis of the critical time predicts the most likely time of the next change of regime to occur in the second half of this month.

We furthermore depict the time series for the New Zealand Index, which has similarly appreciated as the Italian indexes since January, after declining through the last third of 2018, as well.

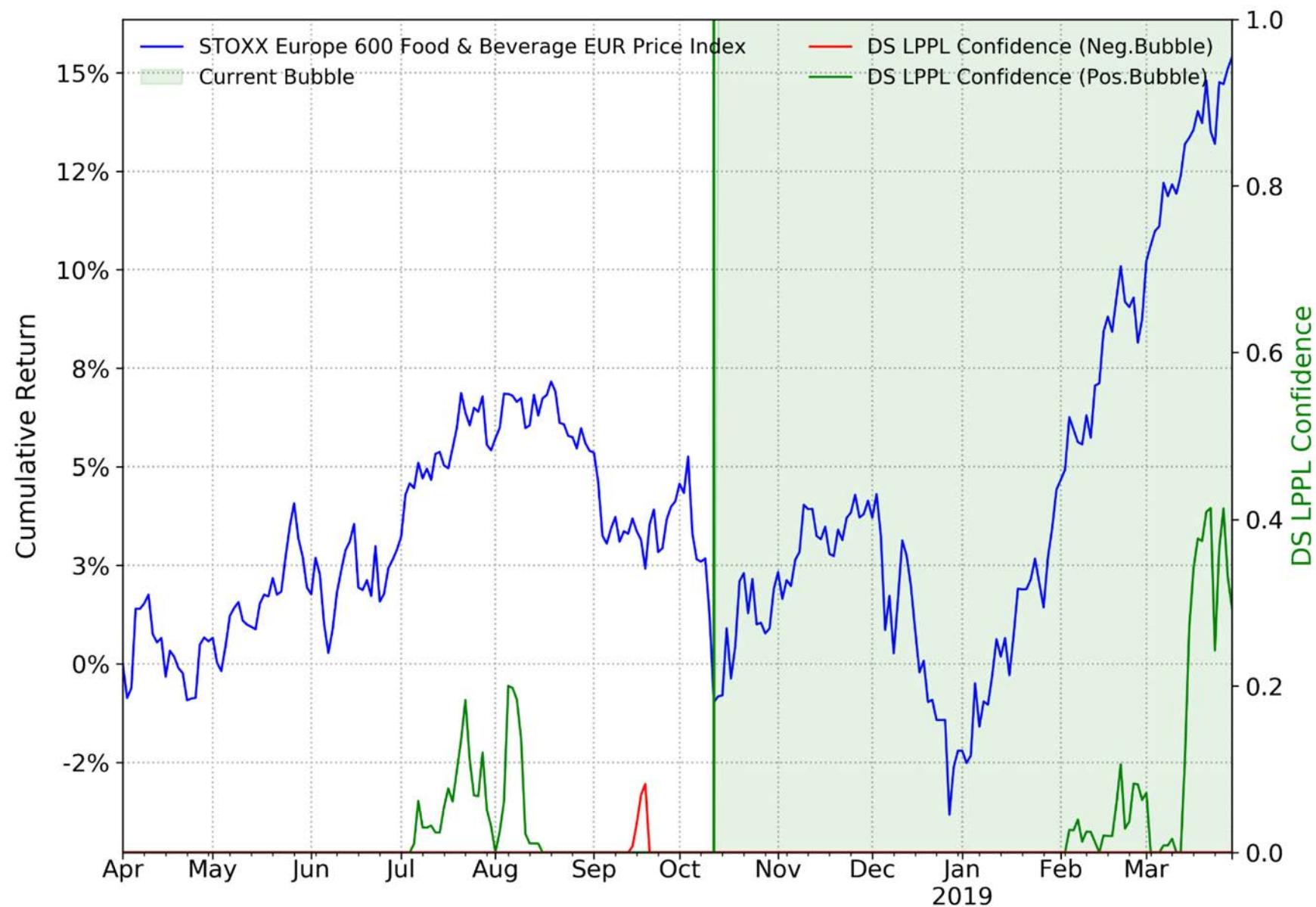


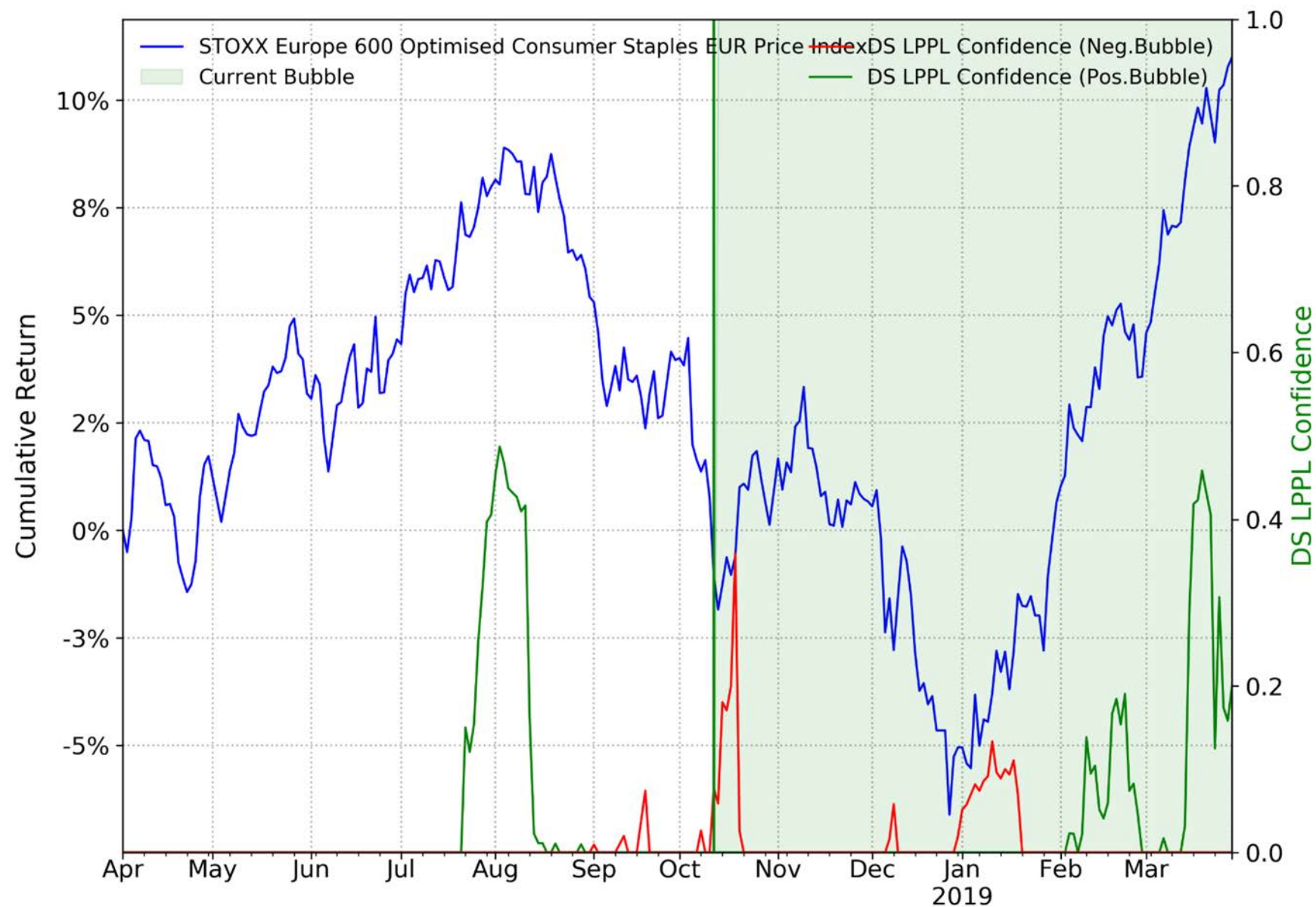


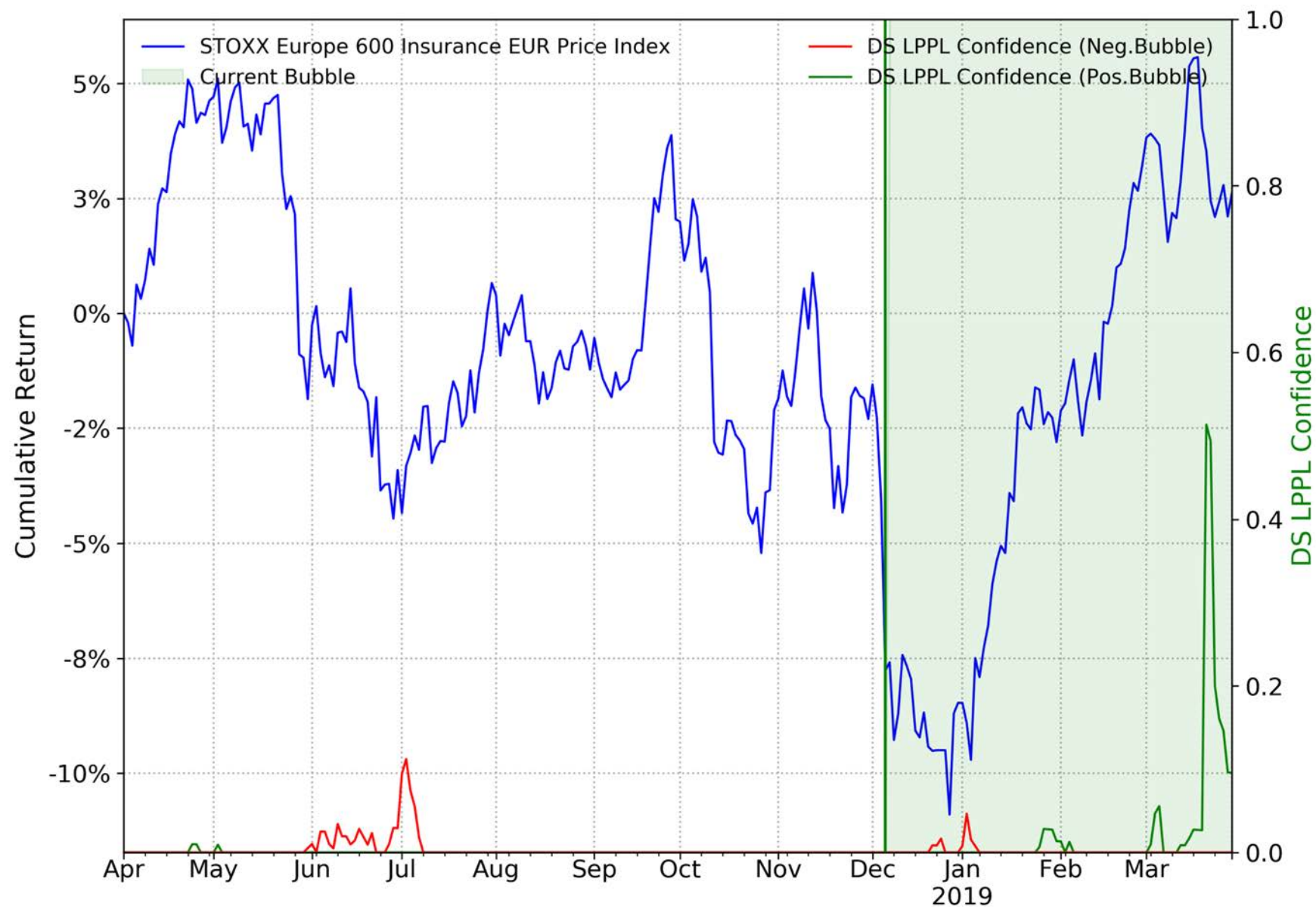
Equities – European Indices

Bubble Data					Cluster Analysis			
Name		Bubble Size bs [%]	Duration $[days]$	DS LPPL Confidence ci [%]	Geometric Average $\sqrt{bs \cdot ci}$ [%]	Critical Time Prediction μ_{t_c}	σ_{t_c} $[days]$	Scenario Probability [%]
Positive Bubbles								
1	STOXX Europe 600 Food & Beverage EUR Price Index	17	169	26	21	2019-08-03	25	58
2	STOXX Europe 600 Optimised Consumer Staples EU...	12	169	34	20	2019-04-08	9	70
3	STOXX Europe 600 Insurance EUR Price Index	11	113	27	18	2019-04-22	1	25
4	STOXX Europe 600 Utilities EUR Price Index	17	168	11	13	2019-05-04	4	61

Focusing purely on European equity indices, we find an increased fraction of positive bubble activity of 12% compared to zero percent the month before. Basically, for all of the reported indices, the signals seem to originate from the recently observed price surge since the beginning of 2019, as already pointed out on the previous slides. Therefore, the reported bubble durations and also the indicator levels are relatively similar. Plots of the time series are given on the next slides.



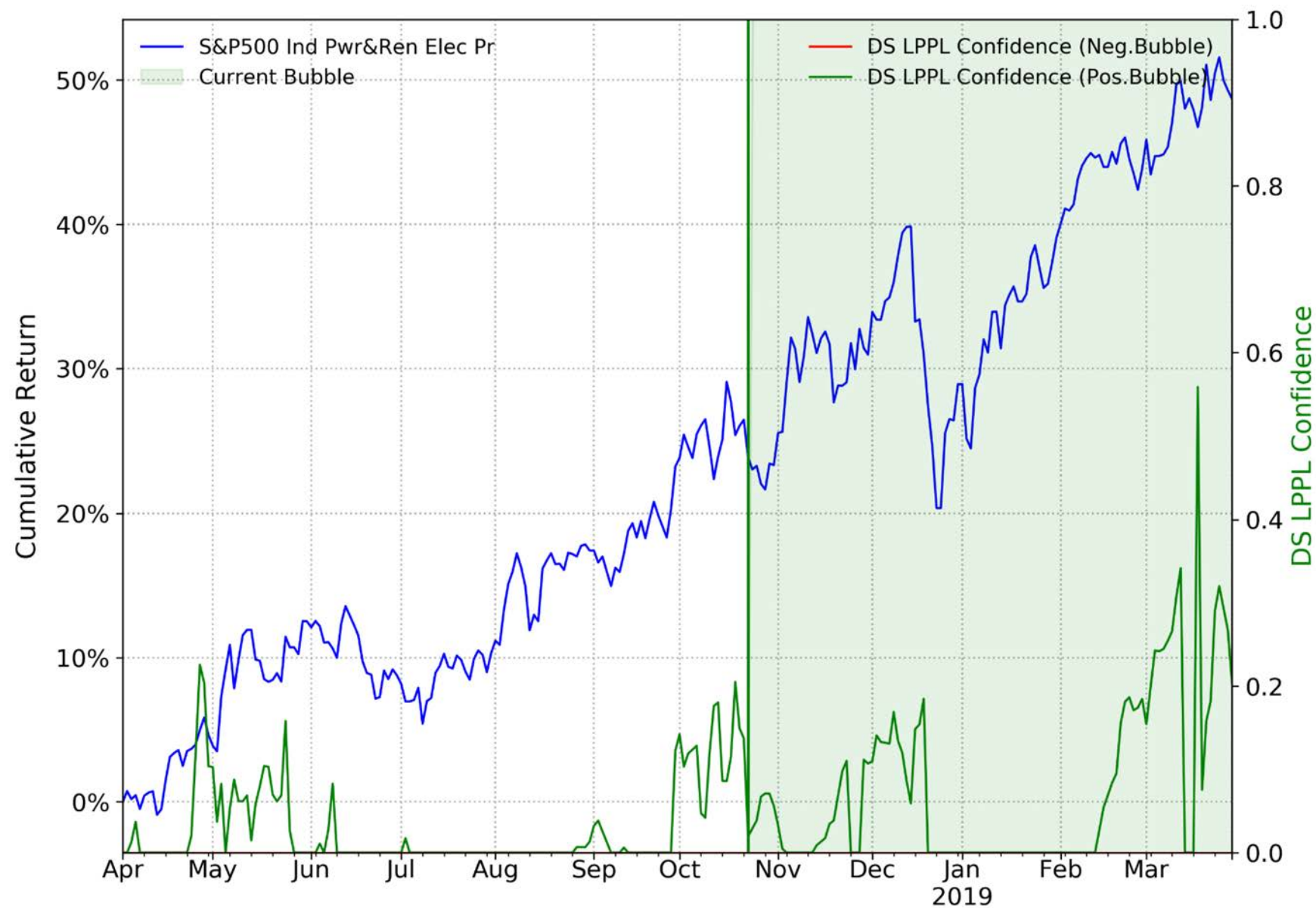


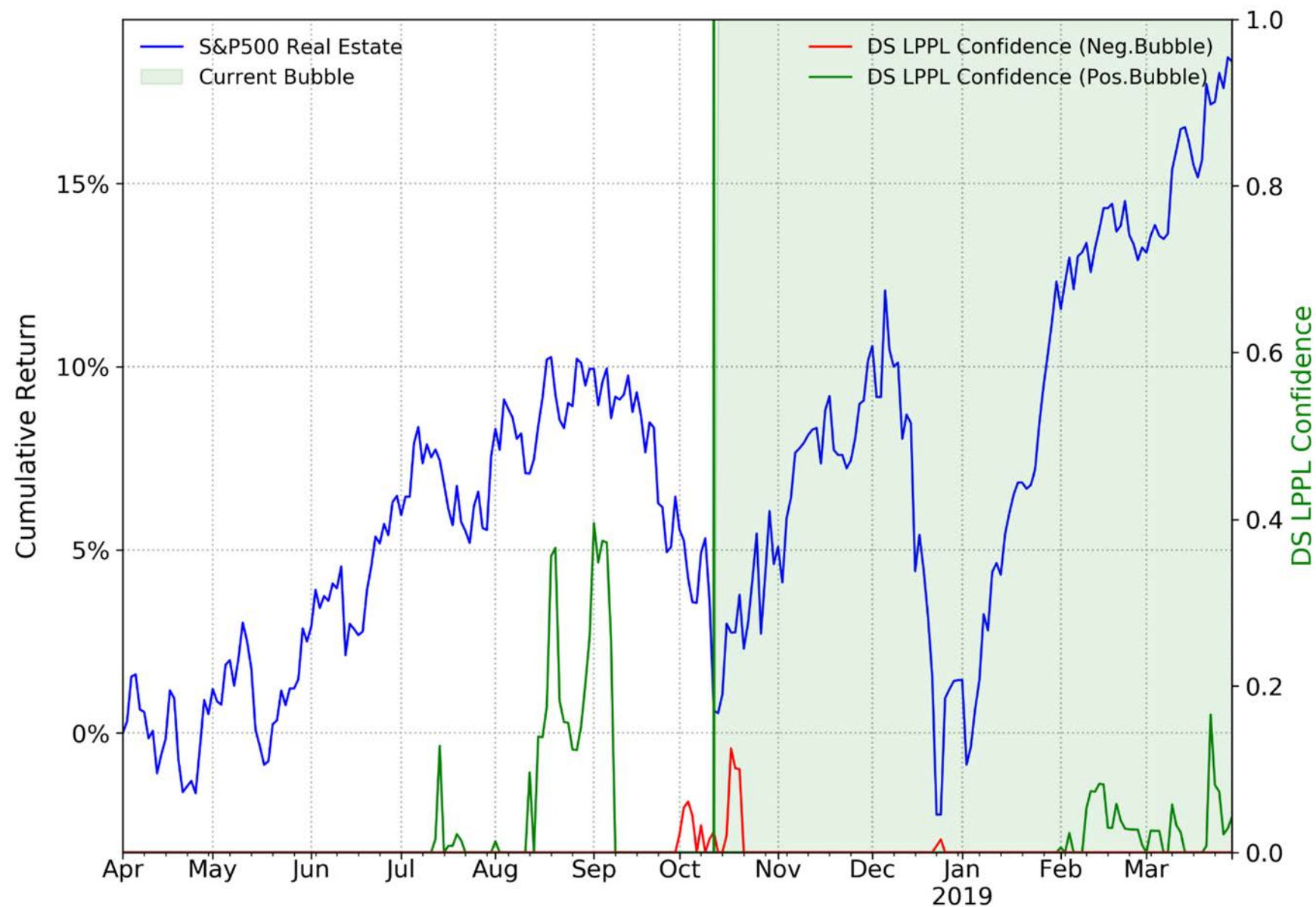


Equities – United States Indices

Bubble Data					Cluster Analysis				
	Name	Bubble Size <i>bs</i> [%]	Duration [<i>days</i>]	DS LPPL Confidence <i>ci</i> [%]	Geometric Average $\sqrt{bs \cdot ci}$ [%]	Critical Time Prediction μ_{tc}	σ_{tc} [<i>days</i>]	Scenario Probability [%]	
Positive Bubbles									
1	S&P500 Ind Pwr&Ren Elec Pr	20	157	38	28	2019-04-03	4	82	
2	S&P500 Ind.Power Prod & Energy Si	20	157	38	28	2019-04-03	4	82	
3	S&P500 Real Estate	18	169	31	23	2019-03-29		74	
4	S&P500 Data Pro&Out Svs	17	170	31	23	2019-04-09	13	73	
5	S&P500 Commercial Serv & Supp In	14	160	34	22	2019-03-30	1	44	

As for the European equities sector, positive bubble activity in the United States equity indices has risen during the past month to now 10% (6% previously). Bubble sizes are between 14-20%, while Confidence Indicator values range from 31% to 38%. The corresponding indicator plots are shown on the following slides. The first depicted index was already presented in the previous report.



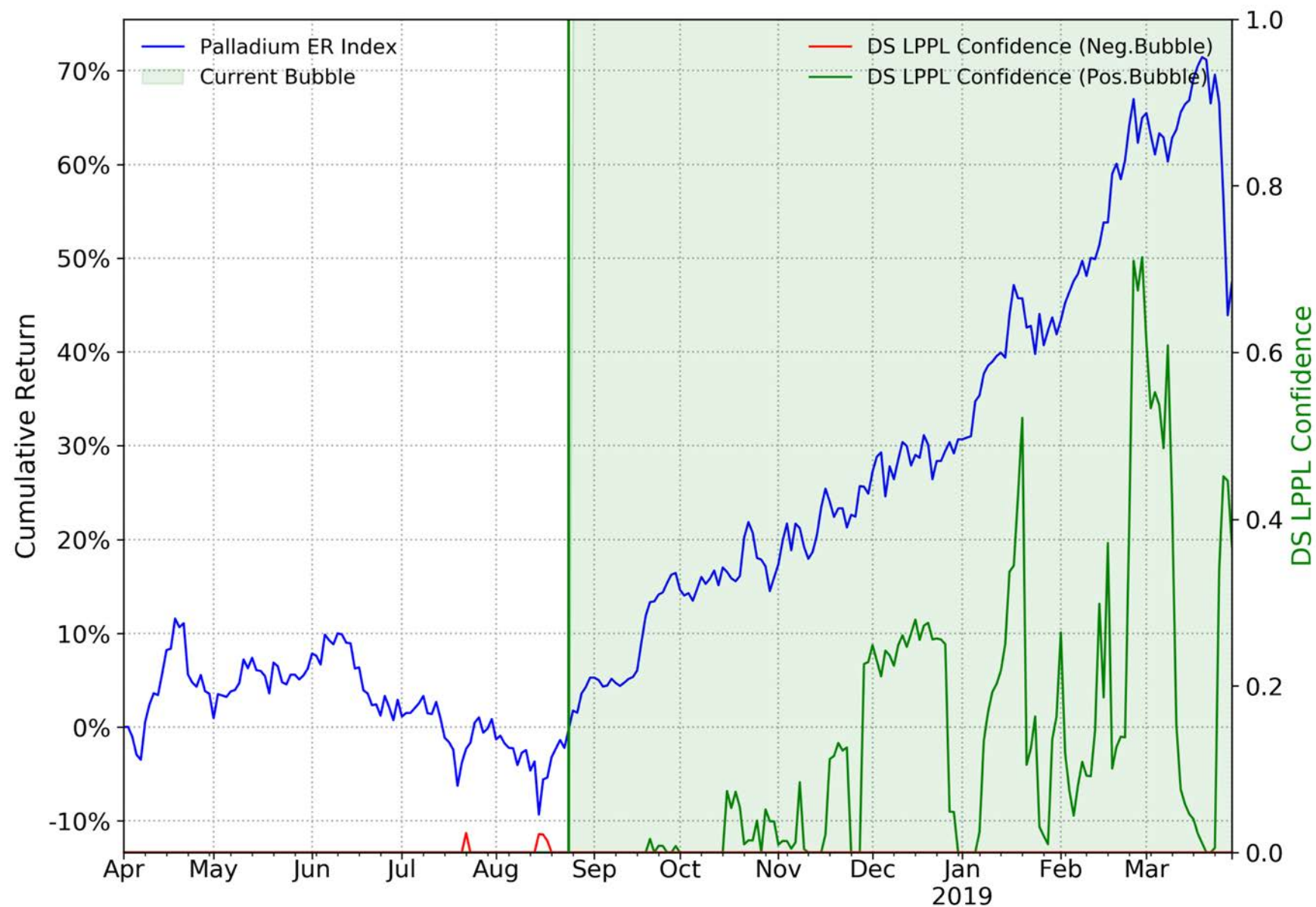


Commodities

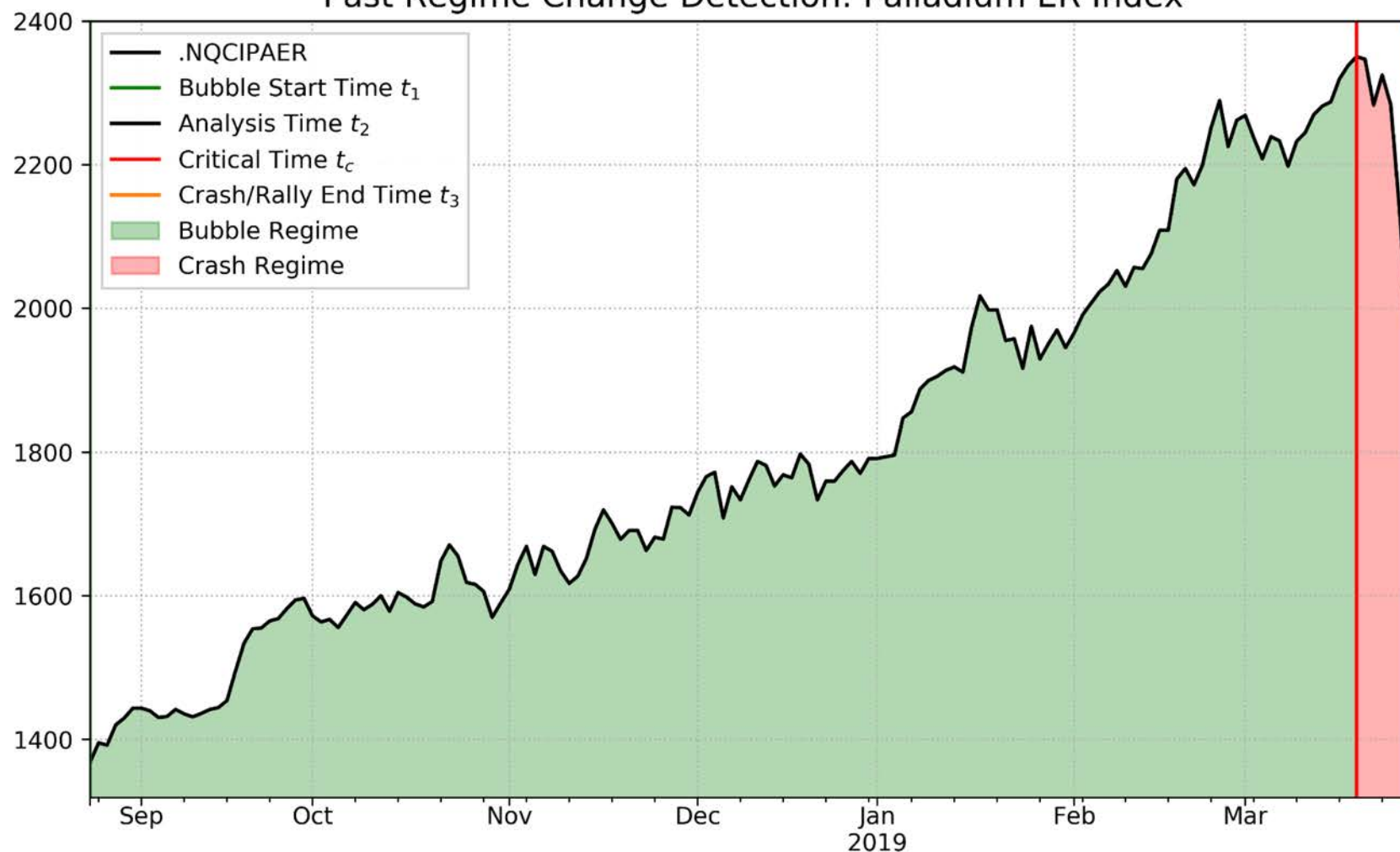
Bubble Data					Cluster Analysis			
	Name	Bubble Size <i>bs</i> [%]	Duration <i>[days]</i>	DS LPPL Confidence <i>ci</i> [%]	Geometric Average $\sqrt{bs \cdot ci}$ [%]	Critical Time Prediction μ_{tc}	σ_{tc} [<i>days</i>]	Scenario Probability [%]
Positive Bubbles								
	1							
Negative Bubbles								
	1	Gasoline ER Index	-23	181	24	23	2019-04-07	15

This month, there are no positive bubble signals in commodities, while one negative bubble signal is detected on the Gasoline Excess Return Index.

Furthermore, the price of Palladium has crashed by more than 15% during March, as predicted in the FCO report of March 1st 2019. The bubble size that was reported in the previous report amounted to 47%. Therefore, we cannot exclude the possibility that the Palladium price will not undergo further declines in the near future. The crash has also been detected by our validation algorithm that searches for past crashes, in order to let us review our former predictions. The standard indicator series plot, as well as a summary of the crash, are provided in the following slides.

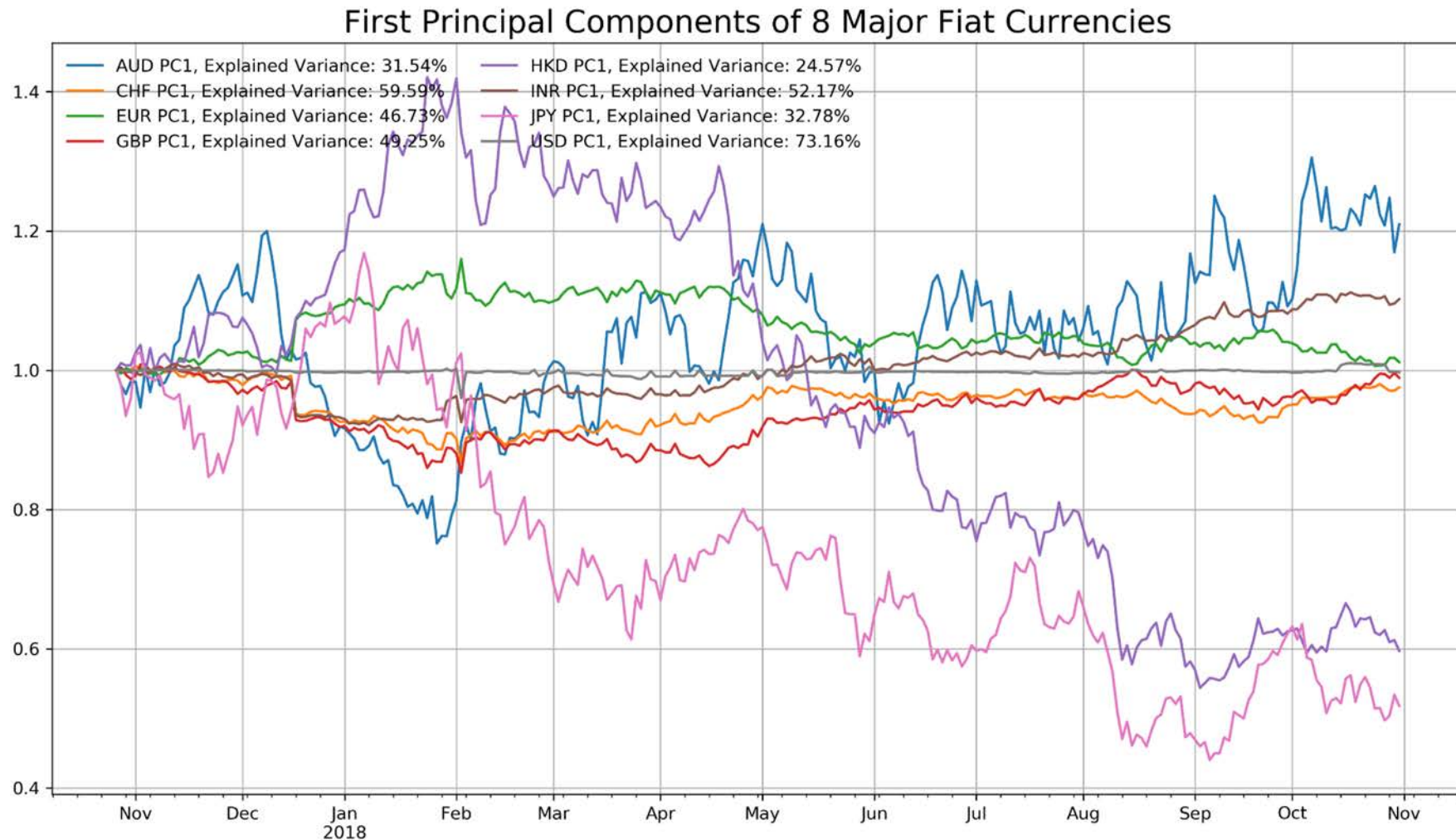


Past Regime Change Detection: Palladium ER Index



Bubble Size = 71.84%, Bubble Duration = 208days, Crash Size = -15.94%

Currencies – PCA



There are no significantly strong signals to report for the forex sector this month. The PCA analysis of the major currencies is shown above.

Cryptocurrencies

	Name	Bubble Size bs [%]	Duration [days]	DS LPPL Confidence ci [%]	Geometric Average $\sqrt{bs \cdot ci}$ [%]	Critical Time Prediction μ_{tc}	σ_{tc} [days]	Scenario Probability [%]
Positive Bubbles								
1	Clams	299	111	72	147	2019-03-31		88
2	Medishares	131	116	87	107	2019-04-07		52
3	Litecoin	147	114	69	101	2019-03-31	1	76
4	Nuls	154	132	62	98	2019-04-01	1	80
5	Blockmason	69	129	94	80	2019-04-19	3	35
Negative Bubbles								
1	Bitcny	-58	140	25	38	2019-04-02	1	53
2	Leocoin	-45	250	23	32	2019-04-18	20	54
3	Bankex	-34	103	19	26	2019-06-20	13	59
4	Achain	-53	232	12	25	2019-09-18	13	46
5	Skycoin	-51	238	11	24	2019-09-19	13	47

A number of crypto-coins are found to exhibit positive and negative bubble activity. As typically expected from the highly volatile crypto-market, the reported bubble sizes are enormous, reaching up to 300%. In addition to these strong magnitudes, the short time scales over which the bubbles form (typically a few months) are exceptional. Due to the short bubble durations, extreme magnitudes and high recurrence of bubbles, it is likely that the reported assets and others may experience repetitive boom-bust-cycles, which makes it risky to invest in these. Overall, it seems like the cryptocurrency sector has recently started to touch bottom and may slowly experience rises in market capitalization, again.

Cryptocurrencies

For complementary recent analyses, see
Revisiting “Are Bitcoin Bubbles Predictable?”: Potential validation &
update. <https://medium.com/@spencerwheatley/revisiting-are-bitcoin-bubbles-predictable-potential-validation-update-b0403acca46a>

which is an update of
Spencer Wheatley, Didier Sornette, Max Reppen, Tobias Huber and Robert N. Gantner, Are
Bitcoin Bubbles Predictable? Combining a Generalised Metcalfe's Law and the LPPLS Model,
Scientific Reports (submitted 15 March 2018), Swiss Finance Institute Research Paper No. 18-
22. Available at SSRN: <https://ssrn.com/abstract=3141050> (<https://arxiv.org/abs/1803.05663>)

See also [the Bitcoin Blog Post on Zero Hedge](https://www.zerohedge.com/news/2018-03-18/are-bitcoin-bubbles-predictable) (<https://www.zerohedge.com/news/2018-03-18/are-bitcoin-bubbles-predictable>)

[Bitcoin Network Researchers See "Substantial" Overvaluation](https://www.bloomberg.com/news/articles/2018-04-02/bitcoin-network-researchers-see-substantial-overvaluation?utm_content=crypto&utm_source=twitter&utm_campaign=socialflow-organic&utm_medium=social), by Janine Wolf, Bloomberg,
April 2, 2018 (https://www.bloomberg.com/news/articles/2018-04-02/bitcoin-network-researchers-see-substantial-overvaluation?utm_content=crypto&utm_source=twitter&utm_campaign=socialflow-organic&utm_medium=social)

[Bitcoin's market value should fall by more than a third before year-end, Swiss researchers say](https://www.cnbc.com/2018/04/02/bitcoins-market-value-should-fall-by-more-than-a-third-before-year-end-swiss-researchers-say.html), CNBC, April 2, 2018 (<https://www.cnbc.com/2018/04/02/bitcoins-market-value-should-fall-by-more-than-a-third-before-year-end-swiss-researchers-say.html>)

[How network theory predicts the value of Bitcoin](https://www.technologyreview.com/s/610614/how-network-theory-predicts-the-value-of-bitcoin/), MIT Technology Review, March 29, 2018
(<https://www.technologyreview.com/s/610614/how-network-theory-predicts-the-value-of-bitcoin/>)

Single Stocks

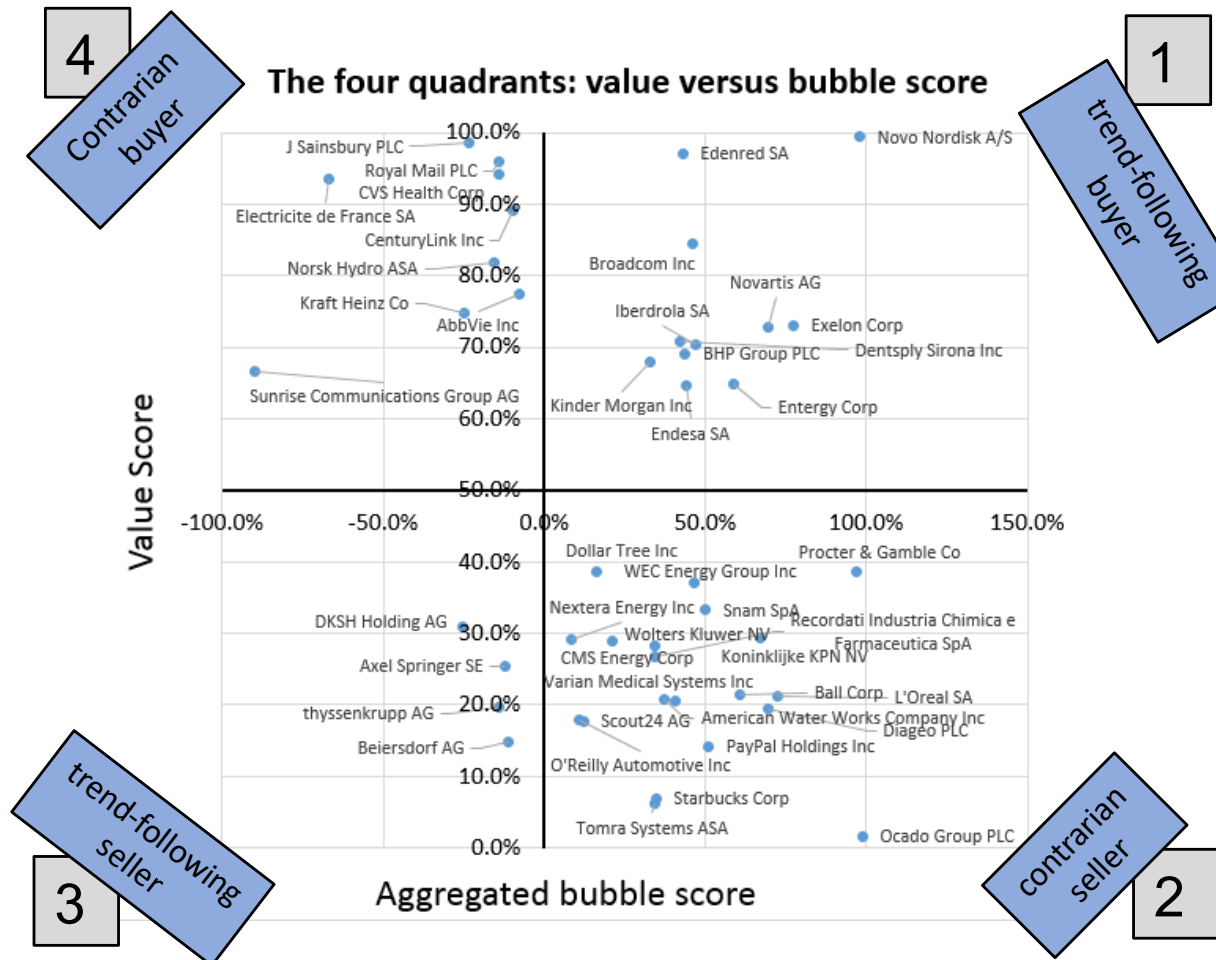
For 801 stocks, we calculate the bubble warning indicators as well as two financial strength indicators, which indicate the fundamental value of the stock and the growth capability respectively.

The stocks are the constituents of the Stoxx Europe 600, the S&P 500 and the Nasdaq 100 indices. From these, all doubles and stocks with incomplete data are removed. Because our financial strength indicators are specifically designed for corporates, all financial institutions are taken out of the set as well.

To analyze the financial strength of individual stocks, we have two indicators. Both scores give a value between zero and one, one being the best of the set and zero the worst, so the higher the score, the higher the financial strength.

- A value score that is based on the ROIC (Return on Invested Capital) taking into account the EV (Enterprise Value) to normalize for high/low market valuations and/or high/low debt; Value scores are calculated by comparing ROIC level versus EV/IC in each industry.
- A growth score that has characteristics similar to the PEG ratio, which is the Price to Earnings ratio normalized by the expected growth of the EPS (Earnings per Share).

Single Stocks



By plotting the value score against the aggregated bubble score, we can divide the stocks into four quadrants*:

1. [Quadrant 1](#): Stocks with a strong positive bubble score and a strong value score (e.g. Entergy Corp);
2. [Quadrant 2](#): Stocks with a strong positive bubble score and a weak value score (e.g. Ocado Group PLC);
3. [Quadrant 3](#): Stocks with a strong negative bubble score and a weak value score (e.g. DKSH Holding AG);
4. [Quadrant 4](#): Stocks with strong negative bubble score and a strong financial strength (e.g. Sunrise Communications Group AG)

*A strong positive bubble signal is identified if bubble score is larger than 10%, and a strong negative bubble signal is identified if bubble score is smaller than -10%.
A strong value score is identified if value score is larger than 60%, and a weak value score is identified if value score is smaller than 40%.

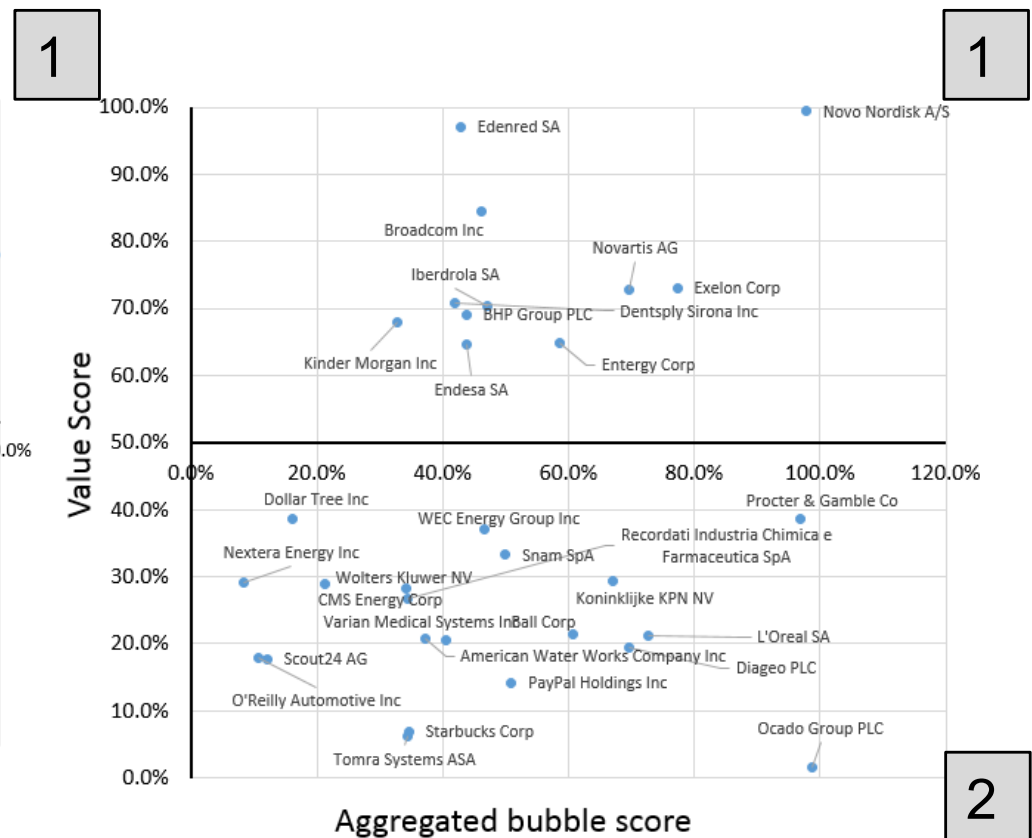
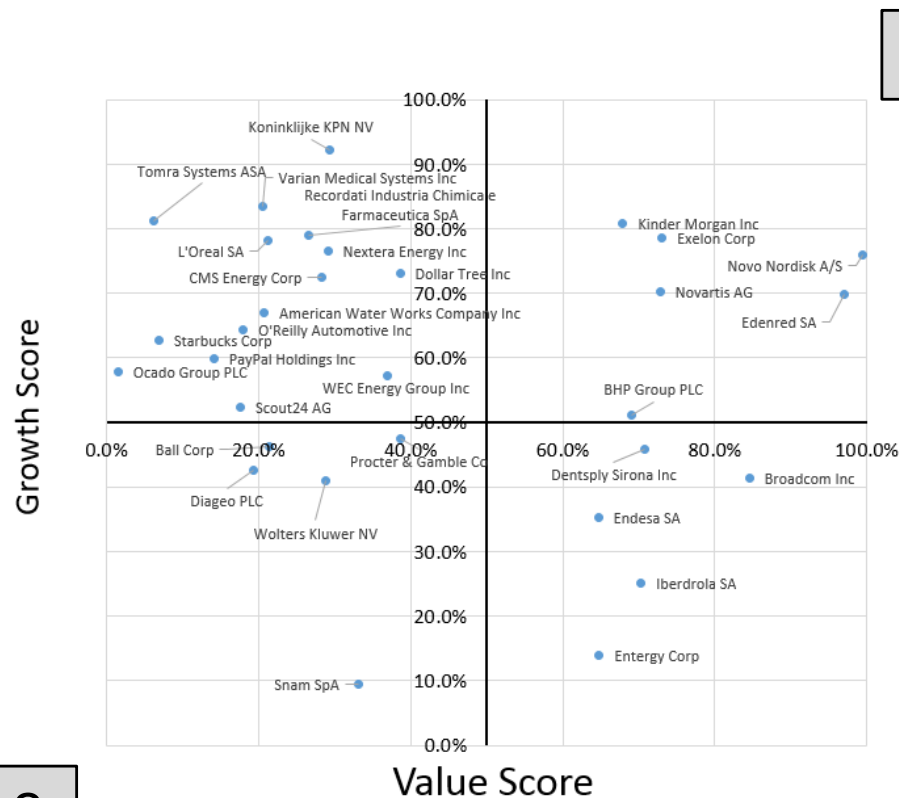
Each quadrant has its own specs:

1. Quadrant 1: Stocks with a strong value score are cheap relative to their earnings potential. The strong positive bubble signal should be interpreted as a momentum indicator possibly the consequence of a repricing based on the fundamentals. *As an investor, one could be a trend-following buyer.*
2. Quadrant 2: Stocks with a weak value score are expensive relative to their earnings potential. The strong positive bubble signal is an indication of sentiment and herding increasing the price until it is not linked to fundamentals anymore. *As an investor, one could be a contrarian seller.*
3. Quadrant 3: These stocks are expensive relative to their earnings potential. On top of that, there are clear negative bubble signals. Such stocks should be considered as falling knives. *As an investor, one could be a trend-following seller.*
4. Quadrant 4: These stocks are cheap relative to their financial performance. The strong negative bubble signal is an indication of sentiment and herding. These stocks can be considered as over-sold. *As an investor, one could be a contrarian buyer.*

Single Stocks

Quadrants 1 and 2 (stocks)

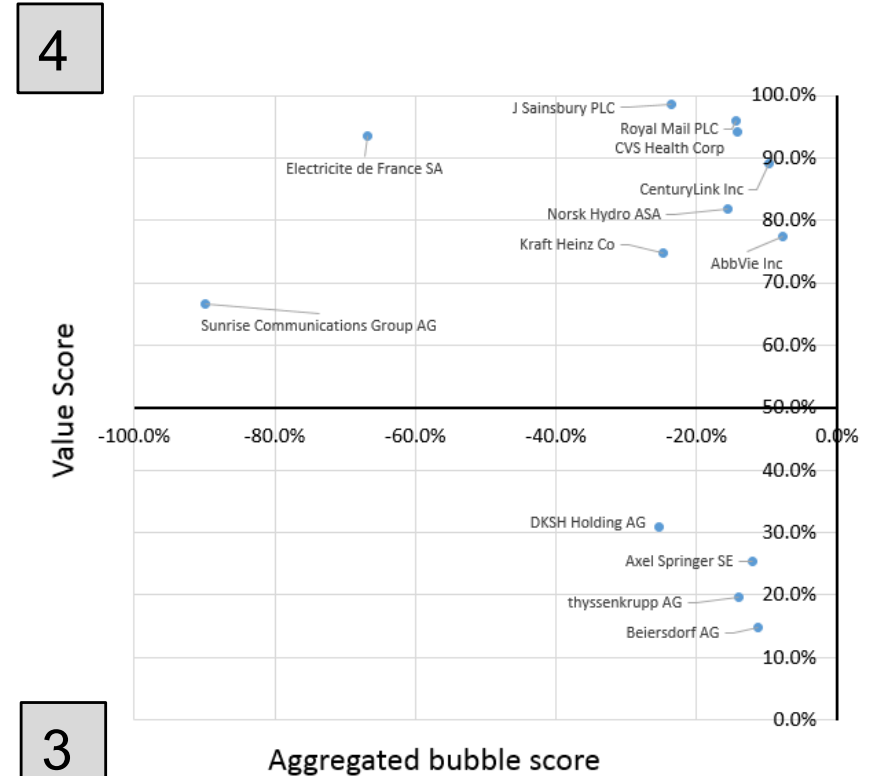
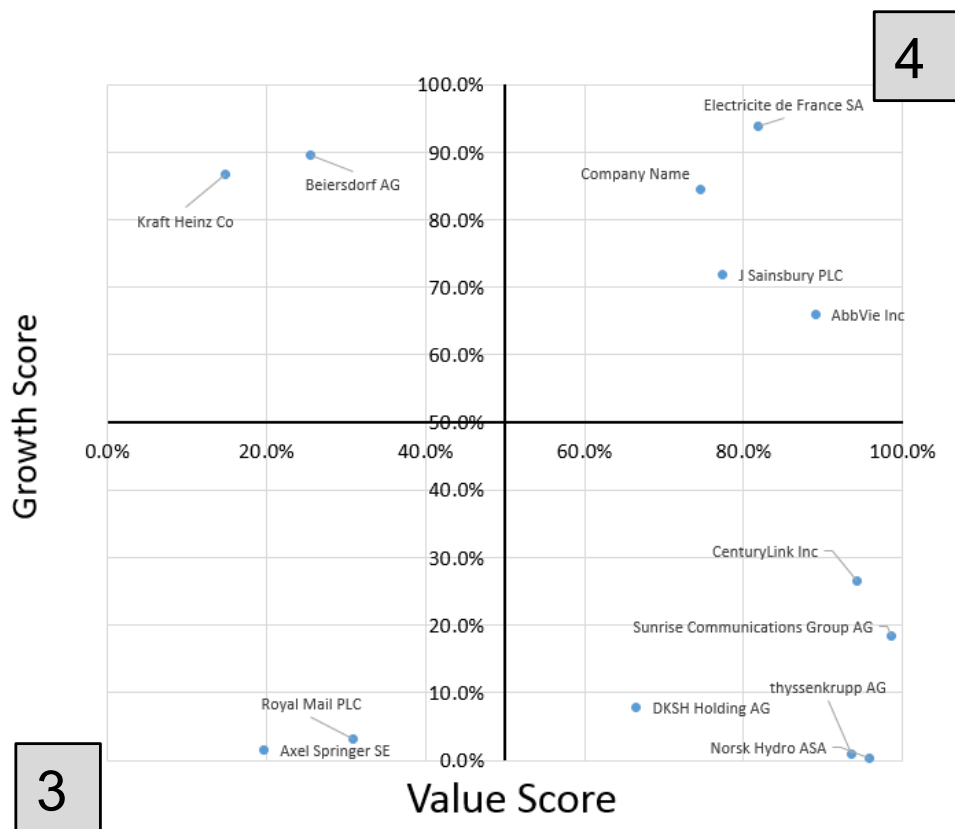
Strong positive bubble signals with strong (respectively weak) fundamentals



Single Stocks

Quadrants 3 and 4 (stocks)

Strong negative bubble signals with weak (respectively strong) fundamentals



Single Stocks

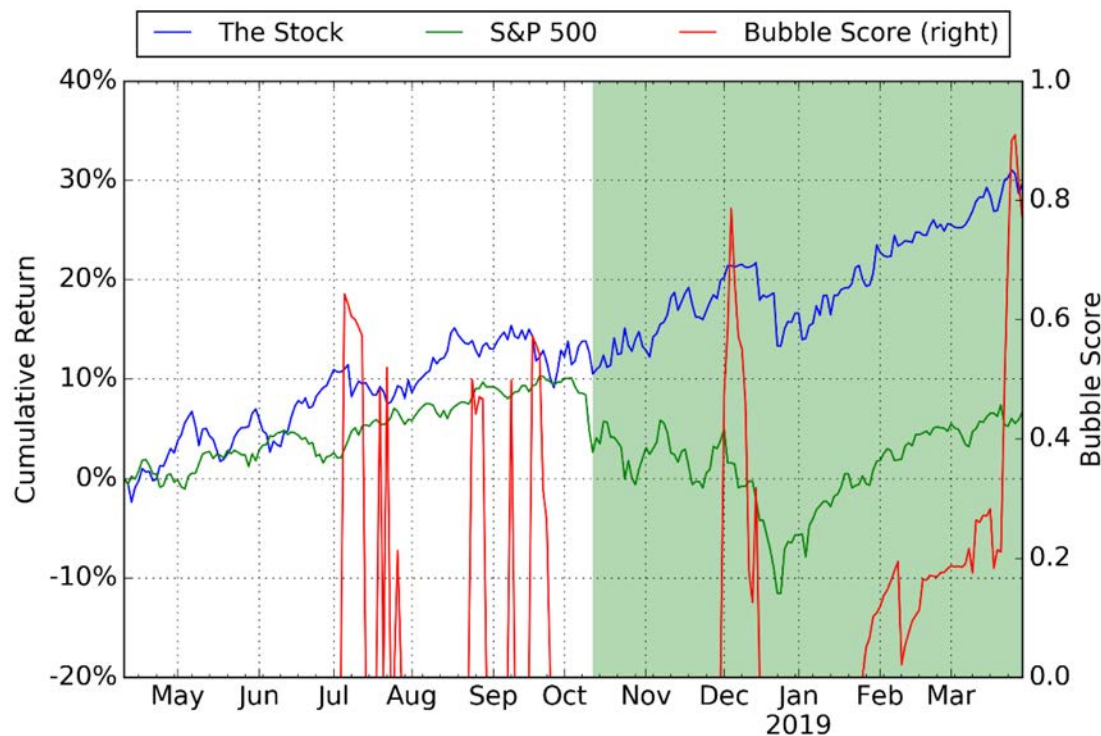
Quadrant 1 stocks: strong positive bubble signals with strong fundamentals

Company Name	Country of Headquarters	GICS Industry Group Name	Yearly Return	Bubble Size	Bubble Start	Bubble Score	Value Score	Growth Score
Broadcom Inc	United States of America	Semiconductors & Semiconductor Equipment	25.6%	43.2%	Jul-18	46.2%	84.5%	41.3%
Dentsply Sirona Inc	United States of America	Health Care Equipment & Services	0.8%	41.5%	Oct-18	42.0%	70.8%	45.8%
BHP Group PLC	United Kingdom	Materials	27.9%	17.5%	Oct-18	43.8%	69.0%	51.1%
Novo Nordisk A/S	Denmark	Pharmaceuticals, Biotechnology & Life Sciences	15.5%	23.9%	Oct-18	97.8%	99.4%	75.9%
Endesa SA	Spain	Utilities	26.1%	26.8%	Oct-18	43.8%	64.7%	35.3%
Iberdrola SA	Spain	Utilities	33.7%	27.8%	Sep-18	47.0%	70.3%	25.1%
Edenred SA	France	Commercial & Professional Services	45.3%	32.5%	Oct-18	42.9%	97.0%	69.8%
Novartis AG	Switzerland	Pharmaceuticals, Biotechnology & Life Sciences	21.7%	17.6%	Aug-18	69.6%	72.8%	70.3%
Entergy Corp	United States of America	Utilities	23.6%	19.3%	Sep-18	58.5%	64.8%	13.9%
Exelon Corp	United States of America	Utilities	32.8%	17.3%	Oct-18	77.3%	73.0%	78.7%
Kinder Morgan Inc	United States of America	Energy	30.4%	21.2%	Oct-18	32.8%	67.9%	80.8%
ICA Gruppen AB	Sweden	Food & Staples Retailing	23.6%	19.6%	43374	36.2%	82.8%	73.7%

Single Stocks - Quadrant 1 stocks

Quadrant 1 stocks: strong positive bubble signals with strong fundamentals

Example: Exelon Corp.

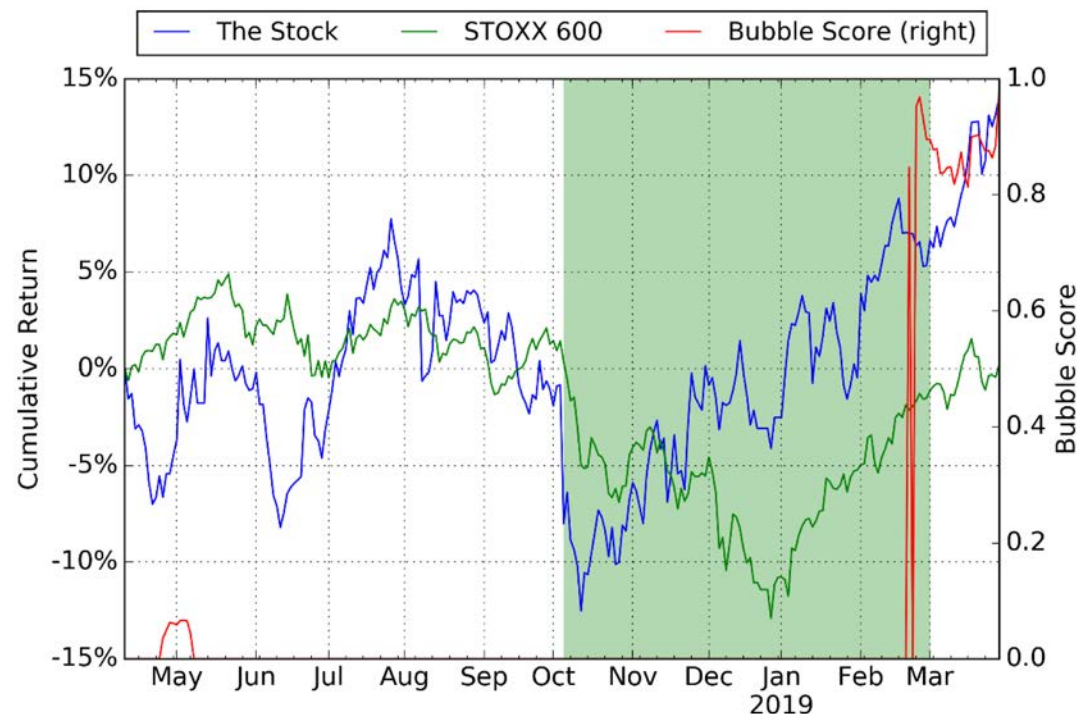


The above graph shows the one year cumulative return of the stock in blue (left hand scale), S&P 500 in green (left hand scale) and the calculated DS LPPLS Bubble Score in red (right hand scale). The green shaded period is the strong positive bubble we identified. The Bubble Score of this six month bubble has reached 77.3% with a bubble size 17.3%.

Single Stocks - Quadrant 1 stocks

Last month example: strong positive bubble signals with strong fundamentals, Novo Nordisk A/S.

The figure below plots the one year cumulative return of the stock (blue), STOXX 600 (green) and LPPLS Bubble Score (red lines on the right y-axis). The green shaded period is the strong positive bubble we identified and reported last month. The stock continued its appreciation in the past month, which is in agreement with the strong fundamentals. The large value of the DS LPPLS indicator implies that one should remain cautious for the approach to a tipping point, as this stock is still identified with a strong bubble signal this month.



Single Stocks - Quadrant 2 stocks

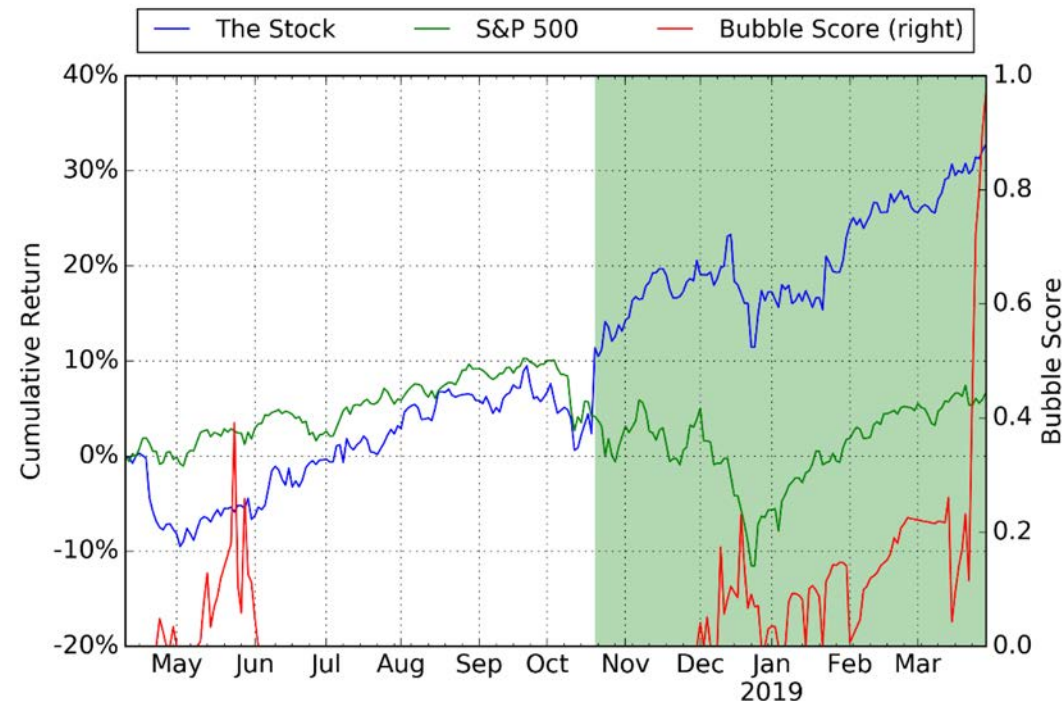
Quadrant 2 stocks: strong positive bubble signals with weak fundamentals

Company Name	Country of Headquarters	GICS Industry Group Name	Yearly Return	Bubble Size	Bubble Start	Bubble Score	Value Score	Growth Score
Dollar Tree Inc	United States of America	Retailing	7.1%	27.2%	May-18	16.1%	38.6%	73.2%
O'Reilly Automotive Inc	United States of America	Retailing	68.9%	23.1%	Aug-18	10.7%	18.0%	64.3%
PayPal Holdings Inc	United States of America	Software & Services	34.1%	25.0%	Oct-18	50.9%	14.1%	59.8%
Starbucks Corp	United States of America	Consumer Services	25.1%	44.0%	Jul-18	34.6%	6.9%	62.8%
Scout24 AG	Germany	Media & Entertainment	13.9%	28.2%	Oct-18	12.1%	17.6%	52.3%
Diageo PLC	United Kingdom	Food, Beverage & Tobacco	25.8%	17.4%	Nov-18	69.6%	19.4%	42.6%
L'Oreal SA	France	Household & Personal Products	25.7%	30.3%	Oct-18	72.6%	21.2%	78.3%
Koninklijke KPN NV	Netherlands	Telecommunication Services	14.1%	24.2%	Sep-18	67.0%	29.3%	92.3%
Wolters Kluwer NV	Netherlands	Commercial & Professional Services	39.6%	21.0%	Oct-18	21.2%	28.8%	40.9%
Recordati Industria Chimica e Farmaceutica SpA	Italy	Pharmaceuticals, Biotechnology & Life Sciences	17.0%	19.3%	Oct-18	34.4%	26.6%	78.9%
Snam SpA	Italy	Energy	19.9%	32.2%	May-18	50.0%	33.2%	9.4%
Tomra Systems ASA	Norway	Commercial & Professional Services	63.5%	34.3%	Oct-18	34.4%	6.2%	81.3%
Ocado Group PLC	United Kingdom	Retailing	166.4%	70.6%	Oct-18	98.7%	1.5%	57.8%
American Water Works Company Inc	United States of America	Utilities	29.3%	22.2%	Jun-18	37.3%	20.7%	66.9%
Ball Corp	United States of America	Materials	42.8%	47.4%	May-18	60.7%	21.3%	46.2%
CMS Energy Corp	United States of America	Utilities	26.3%	19.4%	Jun-18	34.1%	28.3%	72.5%
Nextera Energy Inc	United States of America	Utilities	21.5%	15.9%	Sep-18	8.4%	29.1%	76.7%
Procter & Gamble Co	United States of America	Household & Personal Products	33.8%	19.2%	Oct-18	96.8%	38.7%	47.6%
Varian Medical Systems Inc	United States of America	Health Care Equipment & Services	17.1%	24.2%	Jul-18	40.6%	20.6%	83.5%
WEC Energy Group Inc	United States of America	Utilities	28.5%	15.6%	Oct-18	46.5%	37.0%	57.3%
Yum! Brands Inc	United States of America	Consumer Services	16.4%	20.7%	43221	33.7%	7.1%	88.4%

Single Stocks - Quadrant 2 stocks

Quadrant 2 stocks: strong positive bubble signals with weak fundamentals

Example: Procter & Gamble Co.

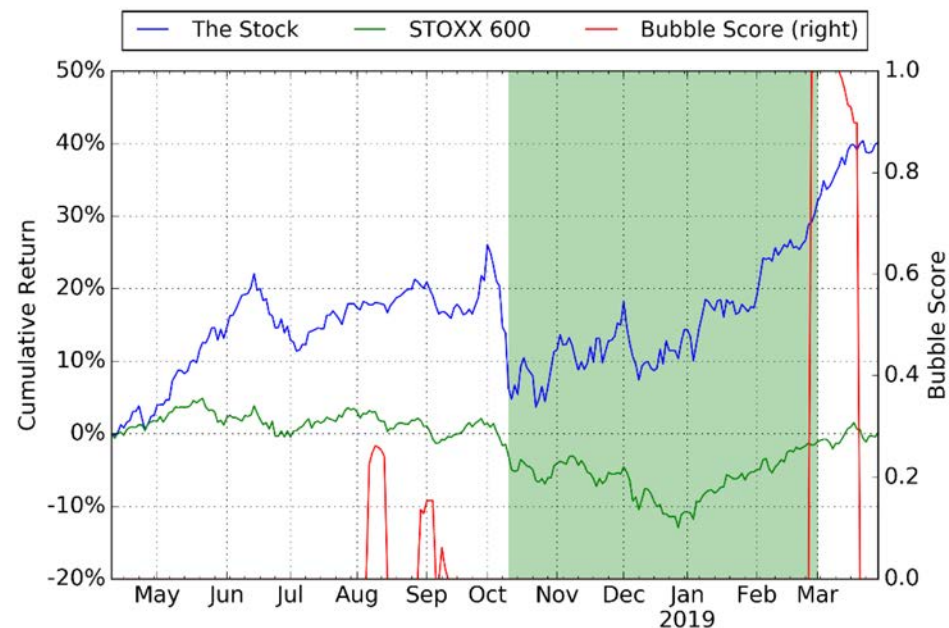


The above graph shows the one year cumulative return of the stock in blue (left hand scale), S&P 500 in green (left hand scale) and the calculated DS LPPLS Bubble Score in red (right hand scale). The green shaded period is the positive bubble we identified. The Bubble Score of this five month bubble has reached 96.8% with a bubble size 19.2%. The strong positive bubble signals and weak fundamentals indicate a high probability of correction in the future.

Single Stocks - Quadrant 2 stocks

Last month example: strong positive bubble signals with weak fundamentals, Halma PLC.

The figure below plots the one year cumulative return of the stock (blue), STOXX 600 (green) and LPPLS Bubble Score (red lines on the right y-axis). The green shaded period is the strong positive bubble we identified and reported in last month. Note that the stock price entered into a change of regime (with a plateau for the time being) after a large draw up during the first half of April. With the weak fundamentals and our DS LPPLS indicator, one should be careful about the strong downside risk of this stock.



Single Stocks - Quadrant 3 stocks

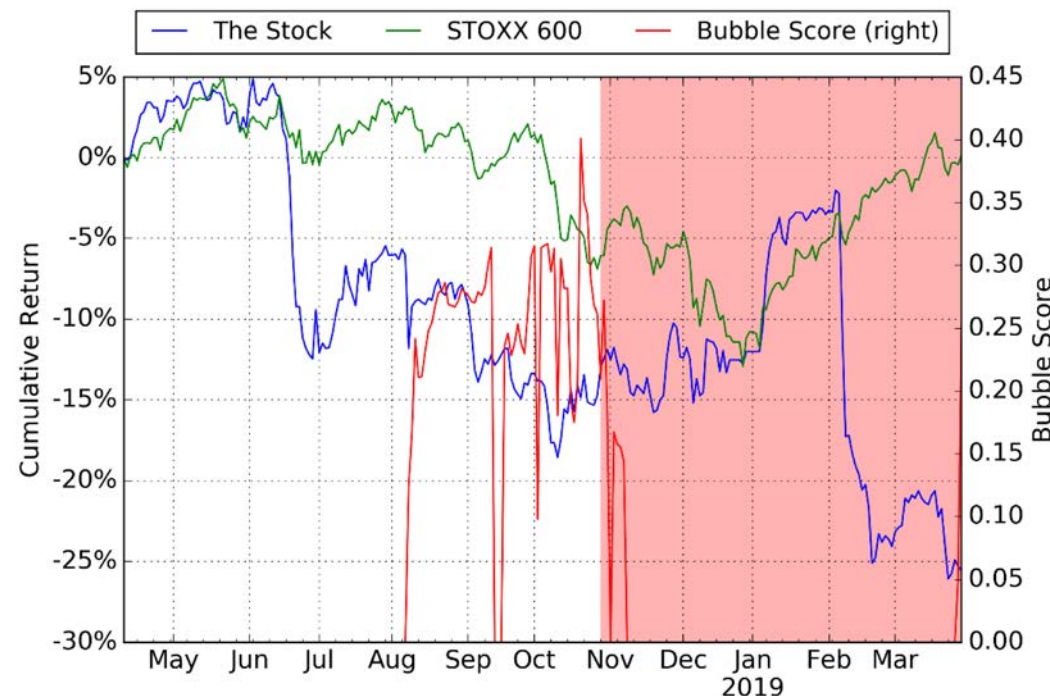
Quadrant 3 stocks: strong negative bubble signals with weak fundamentals

Company Name	Country of Headquarters	GICS Industry Group Name	Yearly Return	Bubble Size	Bubble Start	Bubble Score	Value Score	Growth Score
Beiersdorf AG	Germany	Household & Personal Products	0.2%	-5.5%	May-18	-11.4%	14.9%	86.8%
Axel Springer SE	Germany	Media & Entertainment	-33.3%	-33.3%	Apr-18	-12.0%	25.5%	89.6%
thyssenkrupp AG	Germany	Materials	-44.7%	-39.7%	Aug-18	-14.0%	19.7%	1.6%
DKSH Holding AG	Switzerland	Commercial & Professional Services	-25.6%	-14.5%	Oct-18	-25.3%	31.0%	3.1%

Single Stocks - Quadrant 3 stocks

Quadrant 3 stocks: strong negative bubble signals with weak fundamentals

Example: DKSH Holding AG.

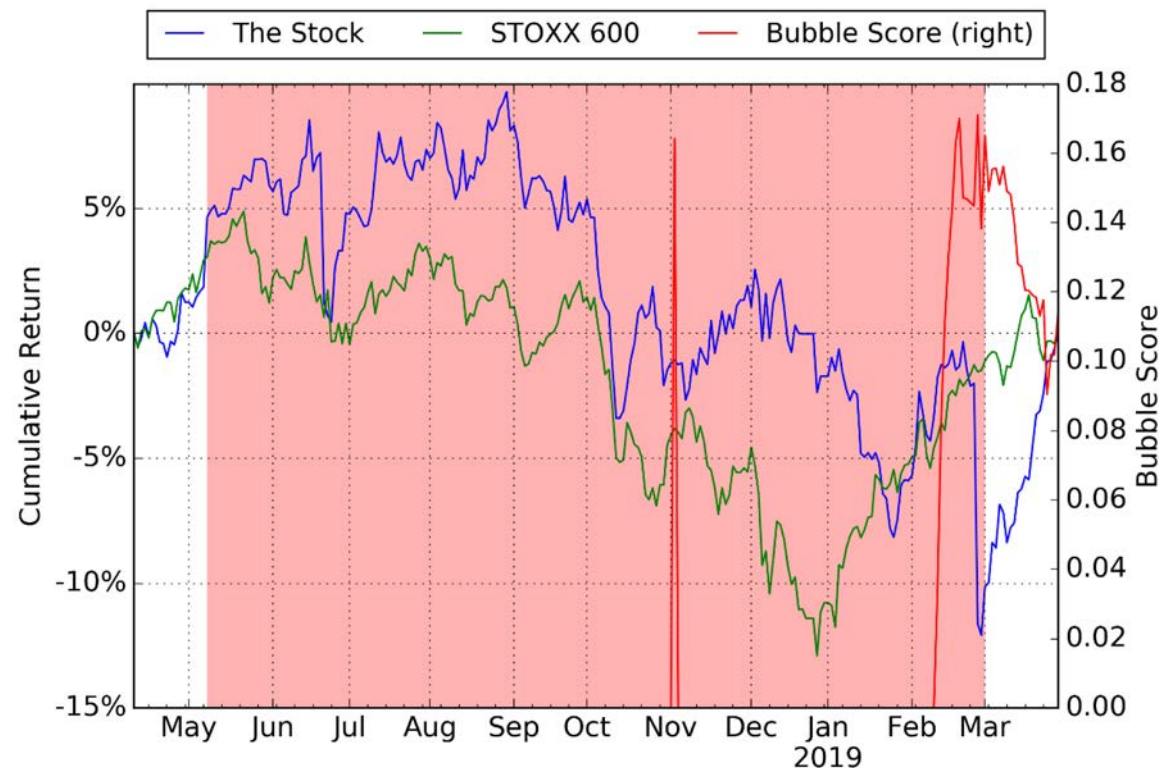


The above graph shows the one year cumulative return of the stock in blue (left hand scale), STOXX 600 in green (left hand scale) and the calculated DS LPPLS Bubble Score in red (right hand scale). The red shaded period is the negative bubble we identified. The Bubble Score of this five month bubble has reached 25.3% with a bubble size -14.5%.

Single Stocks - Quadrant 3 stocks

Last month example: strong negative bubble signals with weak fundamentals, Beiersdorf AG.

The figure below plots the one year cumulative return of the stock (blue), STOXX 600 (green) and LPPLS Bubble Score (red line on the right y-axis). The red shaded period is the strong negative bubble we identified and reported in last month. The stock had a strong rebound in the past month, which is in agreement with the DS LPPLS indicator, notwithstanding the weak fundamentals.



Single Stocks - Quadrant 4 stocks

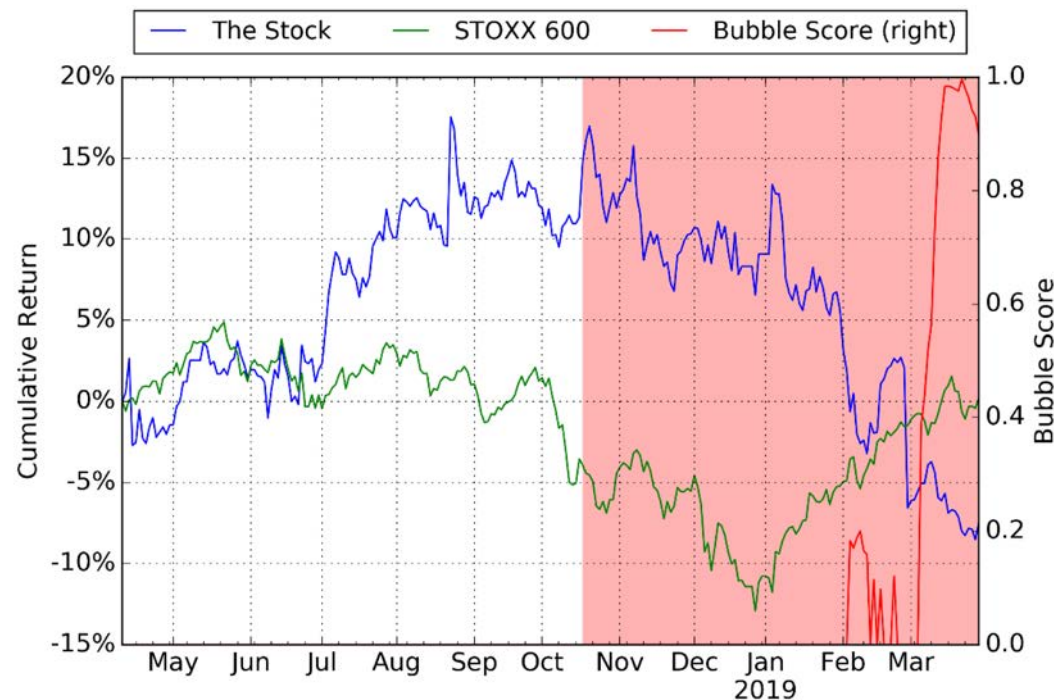
Quadrant 4 stocks: strong negative bubble signals with strong fundamentals

Company Name	Country of Headquarters	GICS Industry Group Name	Yearly Return	Bubble Size	Bubble Start	Bubble Score	Value Score	Growth Score
Kraft Heinz Co	United States of America	Food, Beverage & Tobacco	-46.4%	-40.6%	May-18	-24.7%	74.7%	84.4%
Electricite de France SA	France	Utilities	6.1%	-21.7%	Nov-18	-66.8%	93.5%	0.9%
Norsk Hydro ASA	Norway	Materials	-30.6%	-30.1%	Jun-18	-15.6%	81.9%	93.8%
Royal Mail PLC	United Kingdom	Transportation	-58.3%	-30.9%	Oct-18	-14.3%	95.9%	0.4%
Sunrise Communications Group AG	Switzerland	Telecommunication Services	-9.9%	-19.5%	Oct-18	-89.8%	66.5%	7.7%
J Sainsbury PLC	United Kingdom	Food & Staples Retailing	-6.8%	-30.3%	Aug-18	-23.6%	98.6%	18.4%
AbbVie Inc	United States of America	Pharmaceuticals, Biotechnology & Life Sciences	-12.5%	-15.7%	Jun-18	-7.7%	77.4%	71.9%
CenturyLink Inc	United States of America	Telecommunication Services	-30.5%	-46.4%	Aug-18	-9.7%	89.0%	66.0%
CVS Health Corp	United States of America	Health Care Equipment & Services	-15.7%	-26.3%	Oct-18	-14.3%	94.3%	26.6%

Single Stocks - Quadrant 4 stocks

Quadrant 4 stocks: strong negative bubble signals with strong fundamentals

Example: Sunrise Communications Group AG.

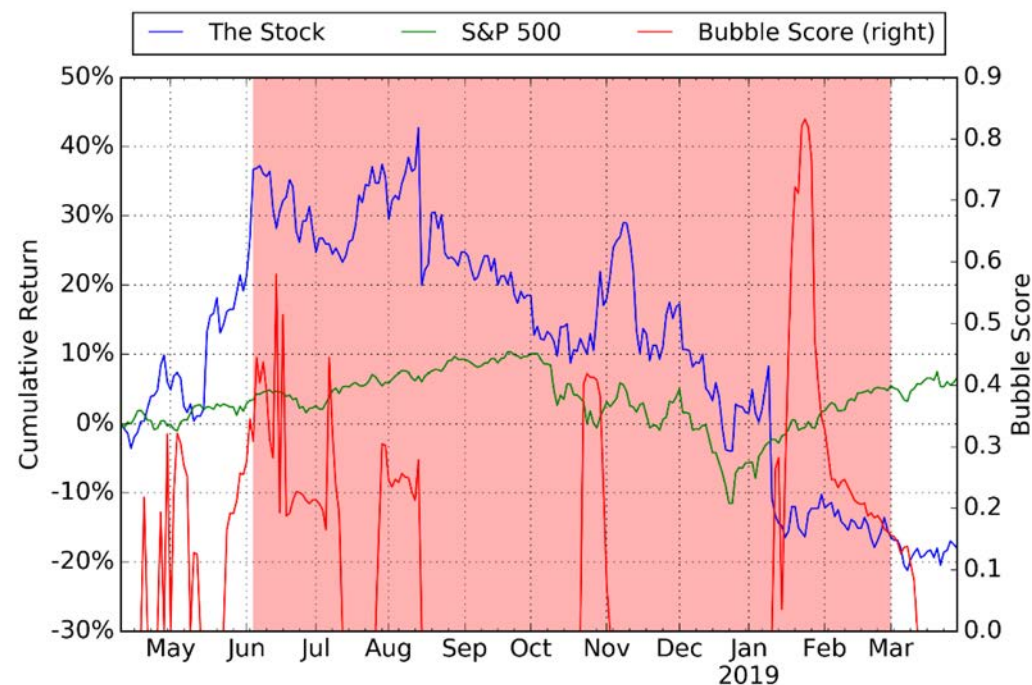


The above graph shows the one year cumulative return of the stock in blue (left hand scale), STOXX 600 in green (left hand scale) and the calculated DS LPPLS Bubble Score in red (right hand scale). The red shaded period is the strong negative bubble we identified. The Bubble Score of this five month bubble has reached 89.8% with a bubble size -19.5%. We expect a rebound in the future, which is due to our diagnostic of a negative bubble signal with strong fundamentals, calling for a contrarian buyer position.

Single Stocks - Quadrant 4 stocks

Last month example: strong negative bubble signals with strong fundamentals, Macy's Inc.

The figure below plots the one year cumulative return of the stock (blue), S&P 500 (green) and LPPLS Bubble Score (red line on the right y-axis). The red shaded period is the strong negative bubble we identified and reported in last month. The stock stopped its drawdown and entered into a plateau in the past month, which is in agreement with our DS LPPLS indicator.



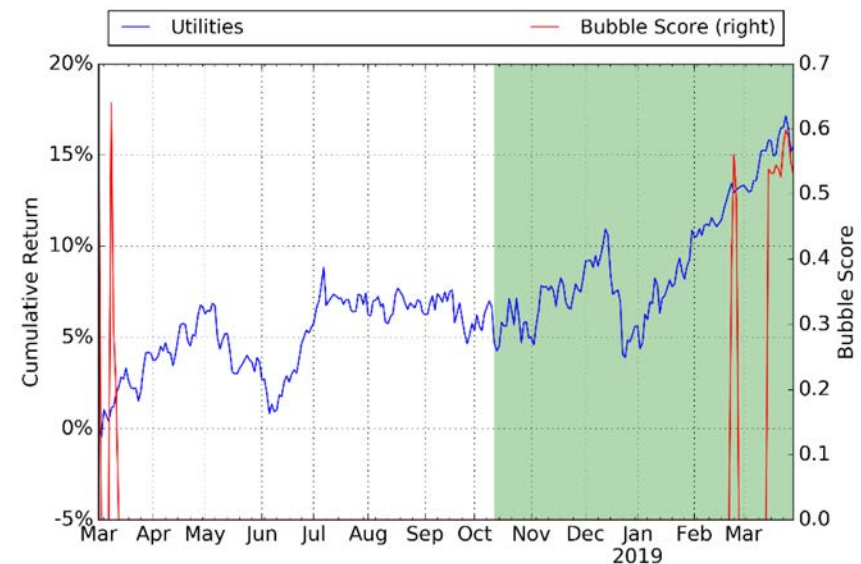
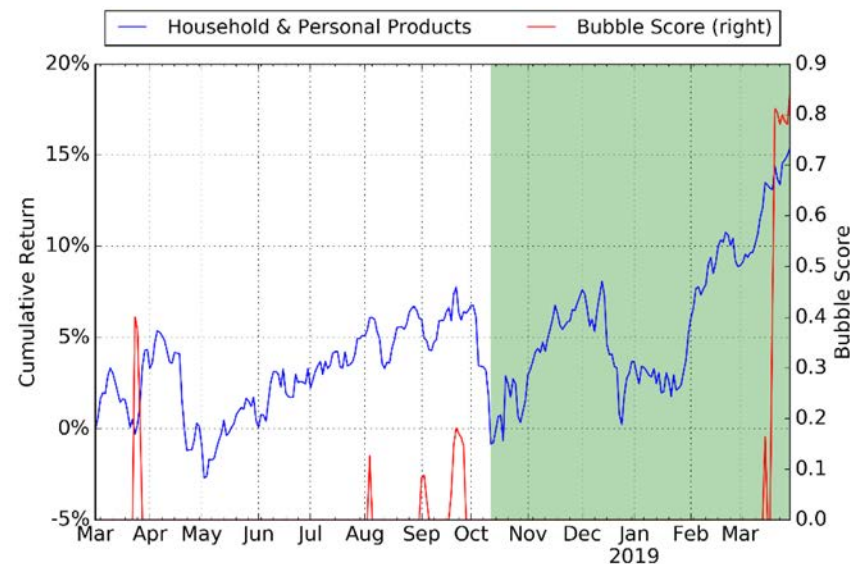
Sectors

GICS Industry Group Name	Yearly Return		Bubble Size		Bubble Score		Value Score		Growth Score	
	Apr 1st	Mar 1st	Apr 1st	Mar 1st	Apr 1st	Mar 1st	Apr 1st	Mar 1st	Apr 1st	Mar 1st
Pharmaceuticals, Biotechnology & Life Sciences	8.6%	6.2%	0.0%	0.0%	0.0%	0.0%	69.9%	68.5%	51.2%	52.6%
Consumer Services	2.3%	-0.7%	0.0%	0.0%	0.0%	0.0%	30.0%	32.4%	50.6%	50.7%
Retailing	13.2%	3.9%	0.0%	0.0%	0.0%	0.0%	20.6%	20.4%	56.3%	55.7%
Transportation	3.9%	1.5%	0.0%	0.0%	0.0%	0.0%	57.7%	57.5%	50.7%	50.7%
Consumer Durables & Apparel	-6.0%	-1.7%	0.0%	0.0%	0.0%	0.0%	37.0%	37.3%	55.4%	59.2%
Semiconductors & Semiconductor Equipment	-4.5%	-11.5%	0.0%	0.0%	0.0%	0.0%	63.6%	64.1%	32.7%	38.7%
Technology Hardware & Equipment	6.9%	-2.0%	0.0%	0.0%	0.0%	0.0%	69.2%	68.9%	43.2%	41.5%
Automobiles & Components	-21.0%	-17.1%	0.0%	0.0%	0.0%	0.0%	74.7%	74.6%	57.8%	56.5%
Telecommunication Services	-4.1%	-6.5%	0.0%	0.0%	0.0%	0.0%	64.4%	67.4%	35.3%	32.3%
Energy	-6.2%	0.3%	0.0%	0.0%	0.0%	0.0%	52.9%	53.2%	49.8%	51.0%
Software & Services	16.0%	6.5%	0.0%	0.0%	0.0%	0.0%	36.8%	37.8%	47.1%	47.1%
Materials	-7.1%	-8.6%	0.0%	0.0%	0.0%	0.0%	53.9%	54.4%	46.7%	46.8%
Health Care Equipment & Services	11.5%	9.0%	0.0%	0.0%	0.0%	0.0%	59.3%	61.8%	50.5%	52.8%
Capital Goods	-5.4%	-6.9%	0.0%	0.0%	0.0%	0.0%	47.4%	46.6%	49.8%	50.7%
Media & Entertainment	15.5%	10.0%	0.0%	0.0%	0.0%	0.0%	36.8%	37.8%	44.3%	43.0%
Commercial & Professional Services	8.4%	6.4%	0.0%	0.0%	0.0%	0.0%	31.4%	34.2%	51.0%	49.8%
Food & Staples Retailing	8.3%	8.5%	0.0%	0.0%	0.0%	0.0%	54.6%	53.6%	52.5%	55.4%
Household & Personal Products	11.3%	7.4%	16.3%	0.0%	84.0%	0.0%	33.7%	37.1%	50.1%	49.5%
Food, Beverage & Tobacco	-1.1%	-6.4%	0.0%	0.0%	0.0%	0.0%	47.3%	48.5%	54.7%	59.0%
Utilities	11.6%	10.3%	10.3%	0.0%	53.2%	0.0%	51.8%	51.6%	46.0%	43.5%
Insurance	-3.3%	-2.8%	0.0%	0.0%	0.0%	0.0%	-	-	-	-
Real Estate	10.7%	4.7%	0.0%	0.0%	0.0%	0.0%	-	-	-	-
Diversified Financials	-9.6%	-11.0%	0.0%	0.0%	0.0%	0.0%	-	-	-	-
Banks	-16.3%	-14.8%	0.0%	0.0%	0.0%	0.0%	-	-	-	-

Sectors

Since Dec 2017, we are using the MSCI World Industry Group Indices to calculate bubble size and bubble score of the corresponding sectors. To determine the value scores and growth scores of the sectors, we average over the corresponding values for each stock of a given sector, weighted by market cap.

This month, we find 2 industry groups with a positive bubble score: *Household & Personal Products*, and *Utilities*, as shown in the figure below. The market expectation of a global economics slowdown can be seen from the recent appreciations of these defensive sectors, which are less dependent on the rise of the economics.



Portfolio Construction & Performance

Here we illustrate the methodology of the portfolio construction process based on the results of our previous analyses.

For individual stocks that we identified in the 4 quadrants, we constructed 4 portfolios based on the 4 quadrants defined in the last report. Each portfolio consists of all the stocks listed in the corresponding quadrant.

(1) Trend-Following Long Stock Portfolio (TFLSP) is made of the stocks that have a **positive** bubble signal as well as a **strong** value score. For instance, TFLSP November consists of all the stocks listed in quadrant 1, identified in slide 37 of November 2017 FCO Report.

(2) Trend-Following Short Stock Portfolio (TFSSP) is made of the stocks that have a **negative** bubble signal as well as a **weak** value score.

(3) Contrarian Long Stock Portfolio (CLSP) is made of the stocks that have a **negative** bubble signal as well as a **strong** value score.

(4) and Contrarian Short Stock Portfolio (CSSP) is made of the stocks that have a **positive** bubble signal as well as a **weak** value score.

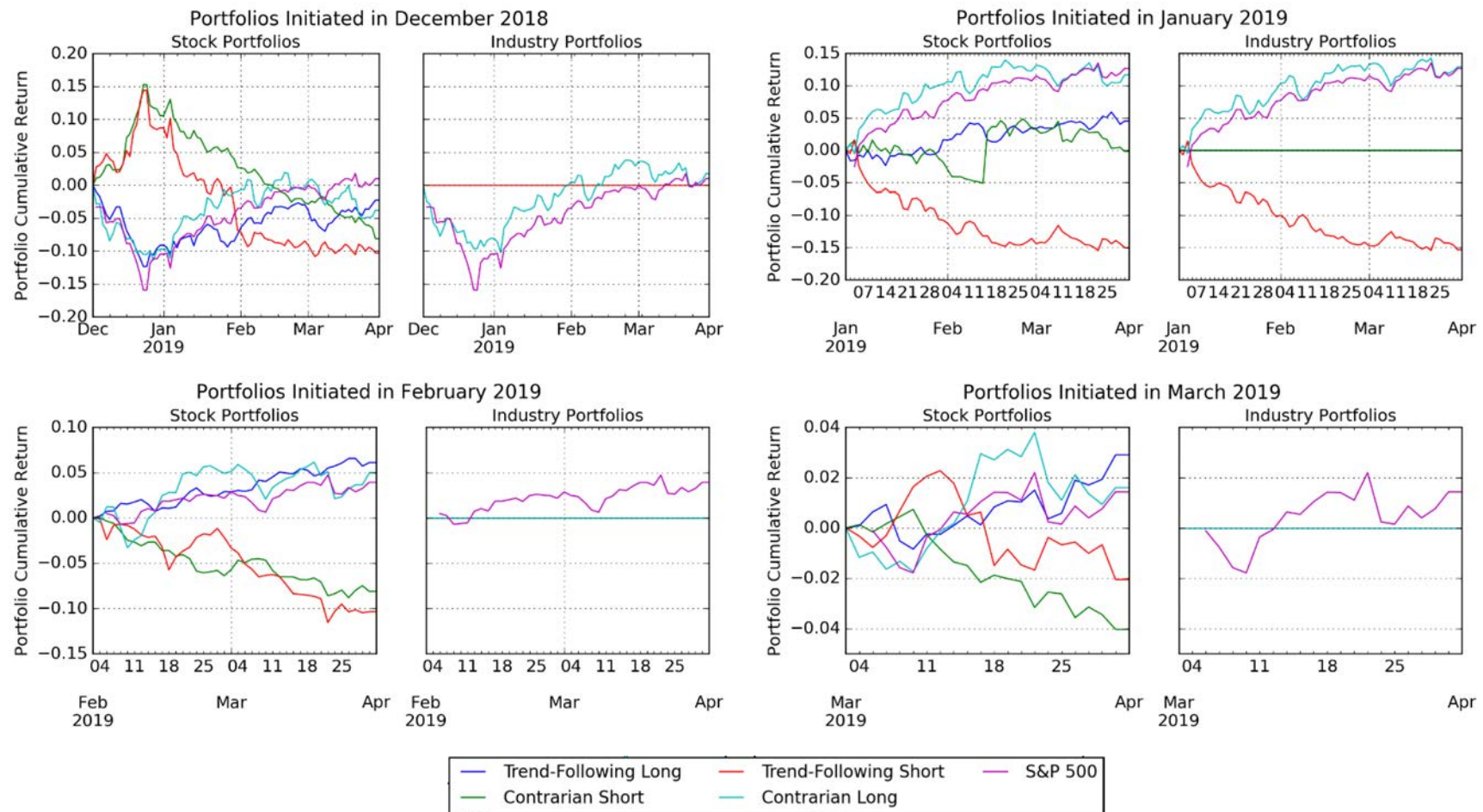
Portfolio Construction & Performance

At the same time, we also classified 20 industries into 4 quadrants, and constructed 4 type of industry portfolios based on the 4 industry quadrants. Each portfolio consists of all the stocks in the industries listed in the corresponding quadrant. Following the same definitions as above, we have Trend-Following Long Industry Portfolio (TFLIP), Trend-Following Short Industry Portfolio (TFSIP), Contrarian Long Industry Portfolio (CLIP), and Contrarian Short Industry Portfolio (CSIP).

In each month, we initiated 8 new portfolios based on the updated results. The performance of every 8 portfolios we initiated since November 2017 are presented in the next slide. All of the stocks in our portfolios are weighted by their market capitalizations and we don't consider transaction cost in the portfolio performance.

Since we started to use a new version of bubble signals and algorithm in November 2017, we only present the portfolios we initiated in November 2017 and later.

Portfolio Construction & Performance



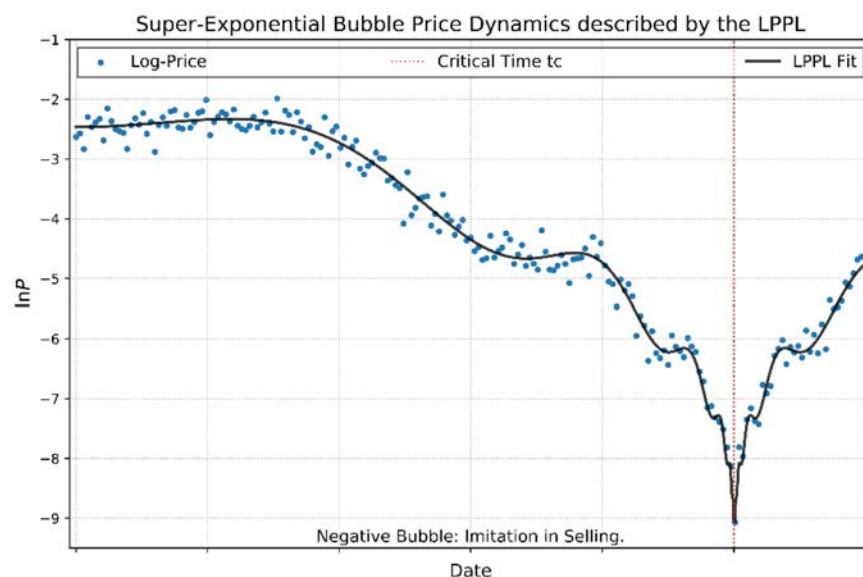
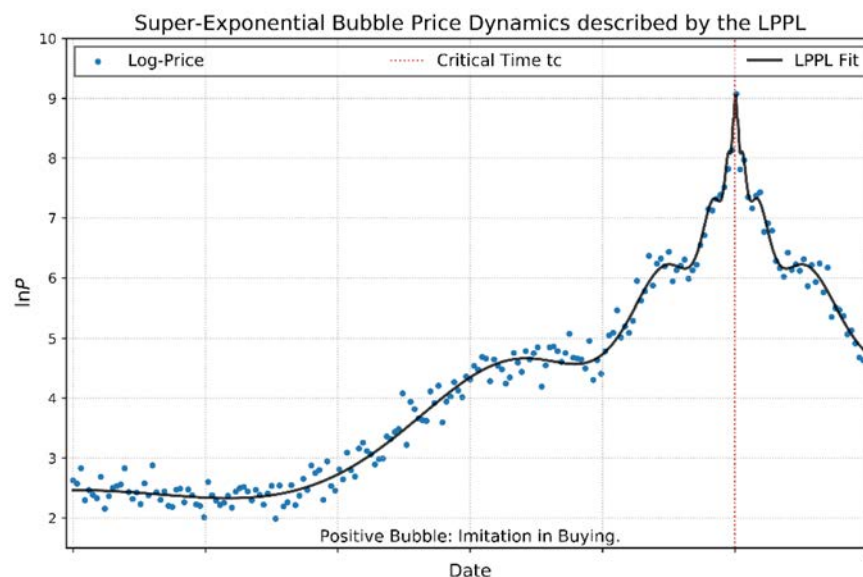
This month, we find that Contrarian Long Portfolios outperformed among others due to the market appreciations in the past months, which contributes to drawdowns of Short Portfolios at the same time. Contrarian Portfolios are more delicate to use due to their sensitivity to timing the expected reversal and exhibit very volatile performances, indicating that most of bubbles in the market are still dominating and that fundamentals have not yet played out. We expect trend-following positions to perform in the months following the position set-up and then contrarian positions to over-perform over longer time scales as the predicted corrections play out.

Appendix

We use the Log-Periodic Power Law Singularity (LPPLS) model to hunt for the distinct fingerprint of **Financial Bubbles**. Basic assumptions of the model are:

1. During the growth phase of a positive (negative) bubble, the price rises (falls) **faster than exponentially**. Therefore the logarithm of the price rises faster than linearly.
2. There are accelerating **log-periodic oscillations** around the super-exponential price evolution that symbolize increases in volatility towards the end of the bubble.
3. At the end of the bubble, the so-called critical time t_c , a finite time singularity occurs after which the bubble bursts.

Together, these effects encompass irrational imitation and herding phenomena amongst market participants that lead to blow-up and instability of asset prices.



The LPPLS Model

Mathematically, the simplest version of the log-periodic power law singularity model that describes the expected trajectory of the logarithmic price in a bubble is given as:

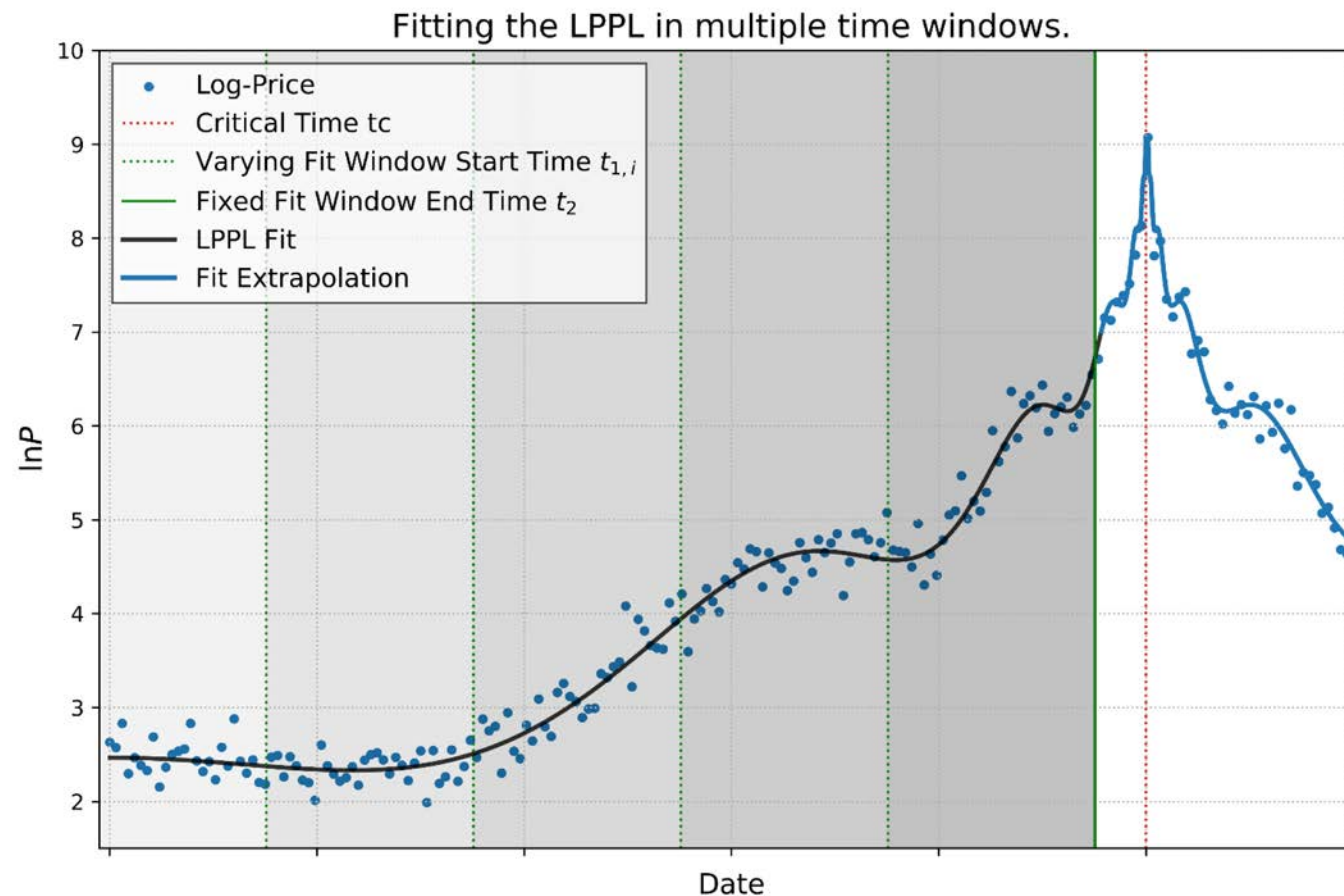
$$LPPLS := E[\ln P(t)] = A + B(t_c - t)^m + (t_c - t)^m [C_1 \cos(\omega \ln(t_c - t)) + C_2 \sin(\omega \ln(t_c - t))]$$

The seven parameters describing the model dynamics are:

- A The finite peak (valley) log-price at the time t_c when the positive (negative) bubble ends.
- m The power law exponent.
- B The power law intensity.
- $C_{1|2}$ Magnitude coefficients of the log-periodic accelerating oscillations.
- ω The log-periodic angular frequency of the log-periodic oscillations.
- t_c The critical time at which the bubble ends.

The set of seven model parameters is obtained by fitting the LPPLS formula to the price time series via a combination of Ordinary Least Squares and nonlinear optimization. The resulting values of the fit parameters reveal whether an asset is in a bubble state. Furthermore, the central parameter of interest, the critical time t_c , may warn of an imminent crash.

LPPLS Analysis of Price Time Series



In order to avoid overfitting and to continuously collect information about price dynamics, we scan asset log-price trajectories for super-exponential price dynamics by sequentially fitting the LPPLS model in different time windows to the underlying price series. The procedure is illustrated in the plot.

For a fixed fit window end time, t_2 , we select different window start times $t_{1,i}$ and fit the LPPL model in each of the resulting windows. This gives one set of calibrated LPPL parameters per fit window. In our monthly report, t_2 , the time of analysis is always the start of the month, i.e. the report date (1st July 2018 for the present report).

The DS LPPL Confidence Indicator

As illustrated on the previous slide, for a fixed analysis time, t_2 , we iteratively perform LPPLS fits over many different window start times $t_{1,i}$. Based on the resulting sets of fit parameters (one per fit window), we determine the bubble start time t_1^* , i.e. the time in the past at which the price (if it did) entered a super-exponential bubble phase from a previous phase of normal price growth. For more information on the determination of the bubble start time, we refer the reader to [1].

Next, we discard all fit results that correspond to windows with start time earlier than the bubble start time t_1^* . Then, we filter parameters in each of the remaining fit calibrations according to filter criteria established in [2]. The imposed filter boundaries are chosen such that only fits with model parameter values that likely correspond to real bubble dynamics are accepted. Such fits are then marked as qualified.

In order to fully capture the information that is contained in the remainder of the calibrations and condense it to a meaningful figure, we have developed the DS LPPLS Confidence Indicator. The indicator is calculated as the number of qualified fits divided by the total number of fits. It quantifies the presence of super-exponential price dynamics obtained over various differently sized time windows. A high value of the indicator signals that LPPLS signatures were detected on many timescales. A low value shows that almost no bubble dynamics were found.

We distinguish between a positive bubble and a negative bubble confidence indicator.

[1] Demos, Guilherme and Sornette, Didier, Lagrange Regularisation Approach to Compare Nested Data Sets and Determine Objectively Financial Bubbles' Inceptions (July 22, 2017). Swiss Finance Institute Research Paper No. 18-20. Available at SSRN: <https://ssrn.com/abstract=3007070> or <http://dx.doi.org/10.2139/ssrn.3007070>

[2] A. Johansen and D. Sornette, Shocks, Crashes and Bubbles in Financial Markets, Brussels Economic Review (Cahiers économiques de Bruxelles) 53 (2), 201-253 (summer 2010) and papers at http://www.er.ethz.ch/media/publications/social-systems-finance/bubbles_and_crashes_theory_empirical_analyses.html

K-means Clustering for Critical Time Prediction

Following the methodology established in Gerlach, Demos and Sornette [1], we employ k-means clustering to our LPPLS calibration results to find possible future scenarios for the ending of a bubble. We are particularly interested in providing a prediction for the critical time t_c which, according to the mathematical definition of the log-periodic power law model, is the time at which we can expect the change of regime in the price of an asset to occur.

As we fit the LPPLS model on many different time window sizes, we often encounter variation in the LPPLS fit parameter sets that are obtained from each fit. The higher the similarity of the resulting parameter sets, the more we trust in their prediction for the critical time parameter. This idea of enhanced believability of results when they repetitively occur on multiple time scales is also the foundation of the DS LPPLS Confidence Indicator.

We detect similar LPPLS fits by applying k-means clustering to the set of LPPLS calibrations over all selected time windows. Here, we report the mean critical times μ_{t_c} and standard deviations σ_{t_c} of the largest such cluster. Furthermore, as complement to the Confidence Indicator, we report the associated scenario probability of the biggest cluster, defined as the number of members in the largest cluster divided by the total number of fits. The scenario probability is therefore a measure similar to the LPPLS Confidence, however with the difference that no constraints are imposed on the parameters to find qualified fits for the LPPLS confidence index.

[1] Gerlach, Demos and Sornette, Didier, Dissection of Bitcoin's Multiscale Bubble History (April 12, 2018). Swiss Finance Institute Research Paper No. 18-30. Available at SSRN: <https://ssrn.com/abstract=3164246> or <http://dx.doi.org/10.2139/ssrn.3164246>

Result Presentation

We present the monthly results of our bubble analysis in the form of a table such as the example given below.

In each table, we separately list assets that are in a positive, respectively, negative bubble state. Furthermore, the table is divided into two sections, bubble data and cluster analysis.

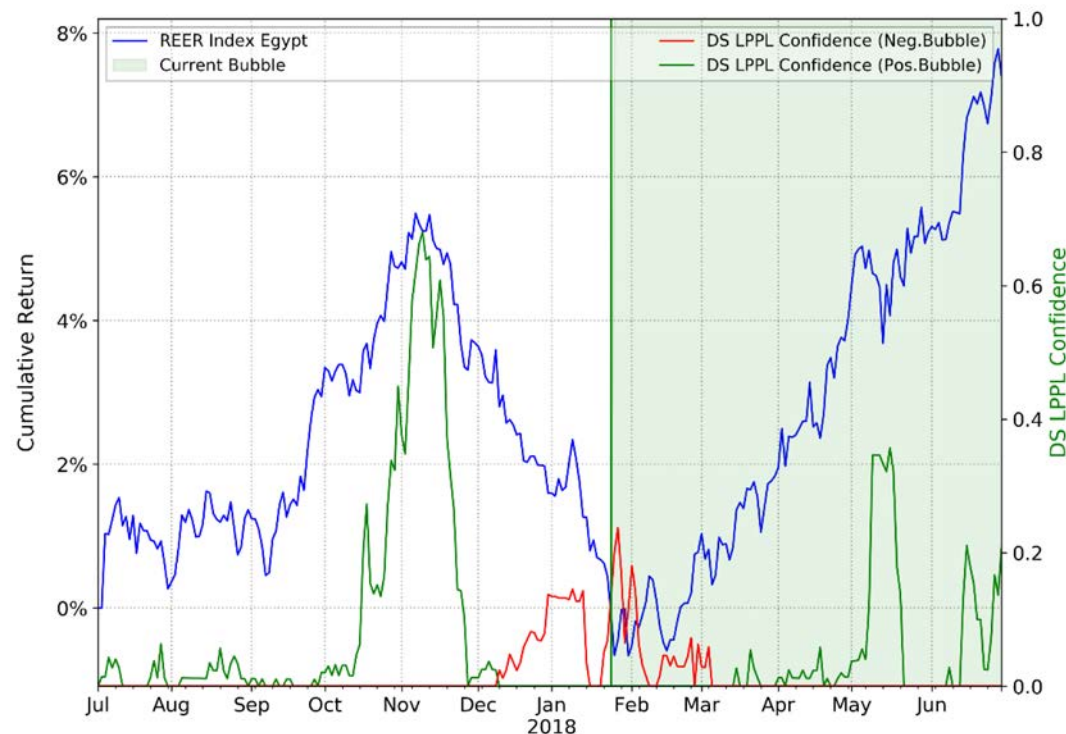
The first section provides asset and estimated bubble characteristics (size and duration), as well as the value of the confidence indicator. We rank assets according to their geometric average of the absolute of bubble size and confidence indicator. In this way, we incorporate the bubble size into the ranking.

In the table section cluster analysis, the prediction data of the two most probable bubble burst scenarios are presented (see previous slide).

Bubble Data					Cluster Analysis			
	Name	Bubble Size bs [%]	Duration [days]	DS LPPL Confidence ci [%]	Geometric Average $\sqrt{bs \cdot ci}$ [%]	Critical Time Prediction μ_{tc}	σ_{tc} [days]	Scenario Probability [%]
Positive Bubbles								
1	iBoxx GEMX Kenya Index	11	276	24	16	2018-07-19	19	62
Negative Bubbles								
1								

Result Presentation

For each asset class, we also supply the confidence indicator time series for the bubble assets listed in the tables. The plot shows the cumulative return (left y-scale, in %) of the analyzed price trajectory (blue) since the beginning of the plot time range. We also plot the time series of the positive (green) and negative (red) DS LPPLS Confidence indicators (right y-scale). The indicator time series are calculated by repetitively applying the procedure described on the slide 'The DS LPPLS Confidence Indicator' over moving window end times t_2 . Furthermore, if, at the last analyzed time, a non-zero indicator value results, i.e. the asset is presently in a bubble state, we outline the time interval for the positive (green shaded) or negative (red shaded) bubble from its beginning to present.



Real Effective Exchange Rate Indices

98 Real Effective Exchange Rate (REER) Indices for different currencies are investigated for bubble characteristics.

The (here CPI-weighted) REER Indices are a measure for the trading competitiveness of the corresponding country.

In contrast to single currency cross rates, the REER is a rather absolute measure of the domestic currency value because it is calculated versus a selection of other currencies.

This has the advantage that, unlike with the methodologies that were used in previous reports, positive and negative bubbles in the value of the currency can clearly be distinguished, as visible in the table above.

Currencies – Principal Component Analysis

As an alternative method to generate a base currency time series from a variety of the currency's cross rates, we apply a principal component analysis (PCA). In total, we perform the PCA for 10 major fiat currencies. For each currency, more than 100 cross rates are grouped into a time series dataset, which, using PCA, is then condensed down into a single time series to which we apply our LPPLS analysis. The time series is assembled according to the weights of the first principal component (PC1) of the dataset. It is used as an aggregate representation of all currency cross rates..

More precisely, taking for instance the Swiss franc as a base currency, we consider $N=100$ currency crosses expressing how much the Swiss franc is valued in these N other currencies. We calculate N time series of returns for the each cross with the base currency (Swiss franc). We then perform a PCA on the dataset of these N return time series. The corresponding PC1 represents the common factor explaining the largest part of the variance of the returns of these N time series. It is interpreted as the embodiment of the real Swiss franc dynamics, filtering out the impact of the other currencies. The LPPLS algorithm is then applied to this equivalent time series.

The plot given in the first part of the report depicts the equivalent time series constructed from the PC1 for each of the ten currency pairs. In the legend, the explained variance of the PC1 is given for each currency. A high explained variance means that most of the crosses of the base currency with other currencies move in a correlated way, which can be interpreted as reflecting a common factor, namely the base currency's intrinsic value dynamics.

To analyze the financial strength of individual stocks in the second part of the report, we have two indicators. Both scores give a value between zero and one, one being the best of the set and zero the worst, so the higher the score, the higher the financial strength.

- A value score that is based on the ROIC (Return on Invested Capital) taking into account the EV (Enterprise Value) to normalize for high/low market valuations and/or high/low debt; Value scores are calculated by comparing ROIC level versus EV/IC in each industry.
- A growth score that has characteristics similar to the PEG ratio, which is the Price to Earnings ratio normalized by the expected growth of the EPS (Earnings per Share).

Visit the Financial Crisis Observatory for more information

<http://www.er.ethz.ch/financial-crisis-observatory.html>