The FCO Cockpit
Global Bubble Status Report

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Contents

About

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.

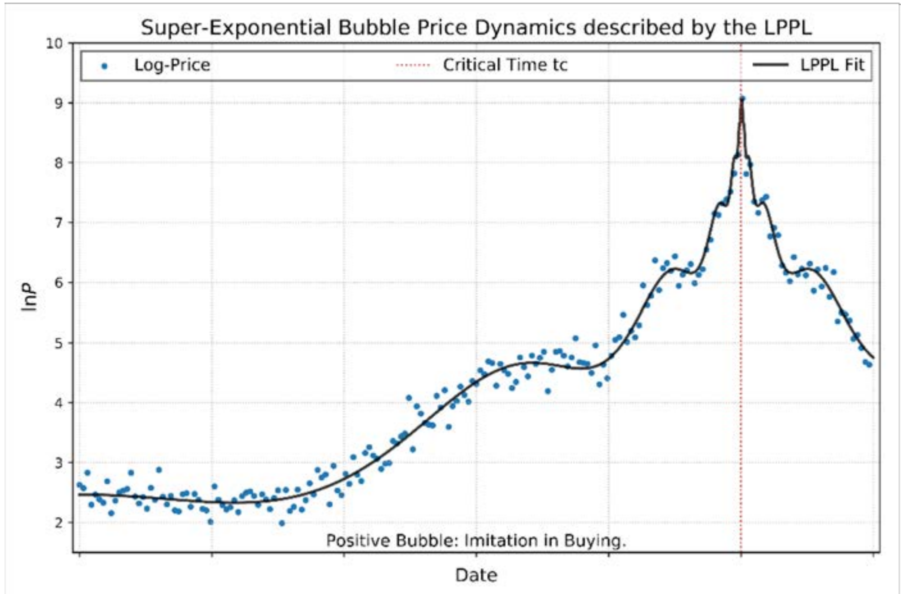
For an intuitive explanation of the methodology and the specifics of the indicators that are used in this report, we refer to: D. Sornette and P. Cauwels, Financial bubbles: mechanisms and diagnostics. Review of Behavioral Economics 2 (3), 279- 305 (2015)
http://arxiv.org/abs/1404.2140 and http://ssrn.com/abstract=2423790

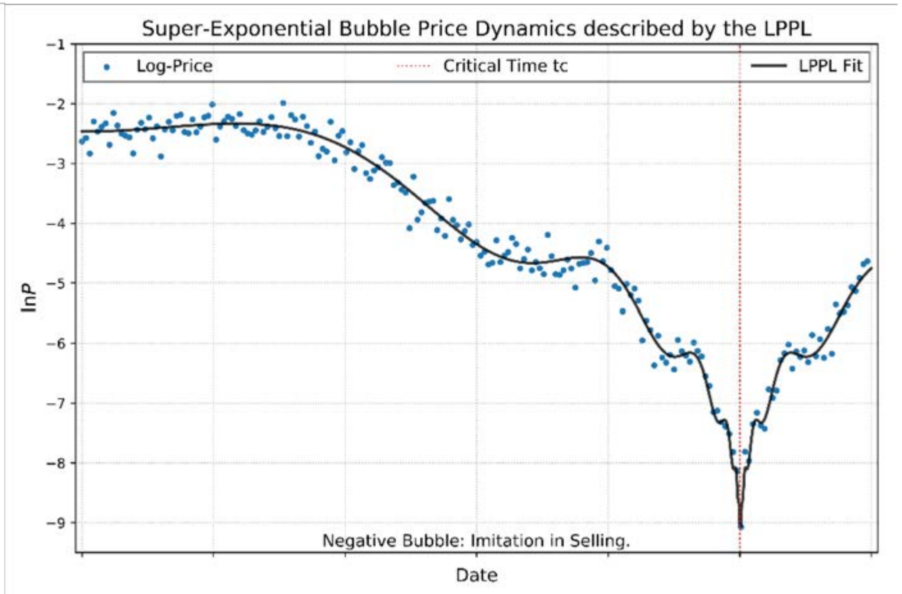
Methodology

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:

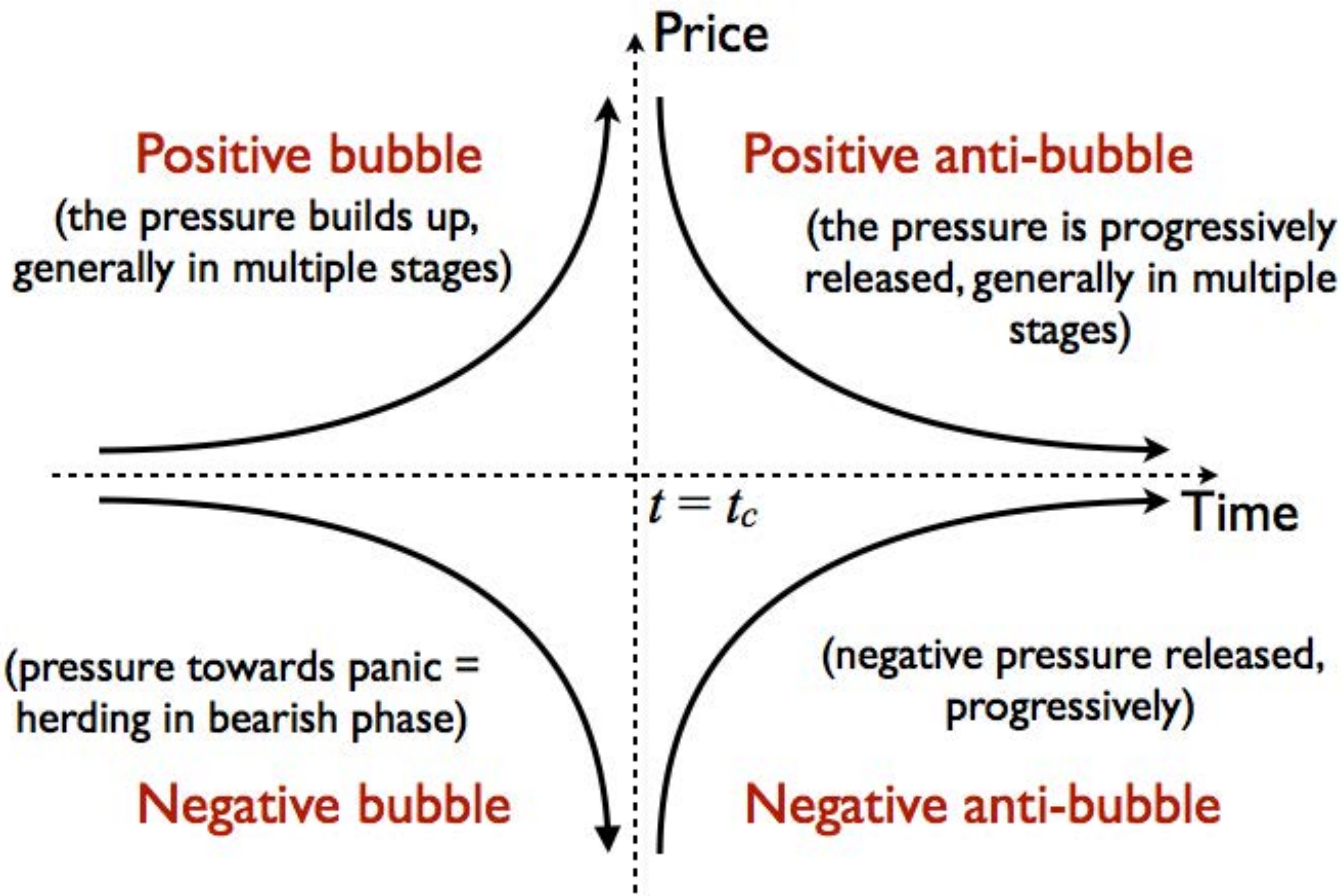
1. During the growth phase of a positive (negative) bubble, the price rises (falls) faster than exponentially. Therefore the logarithm of the price rises faster than linearly.
2. There are accelerating log-periodic oscillations around the super-exponential price evolution that symbolize increases in 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

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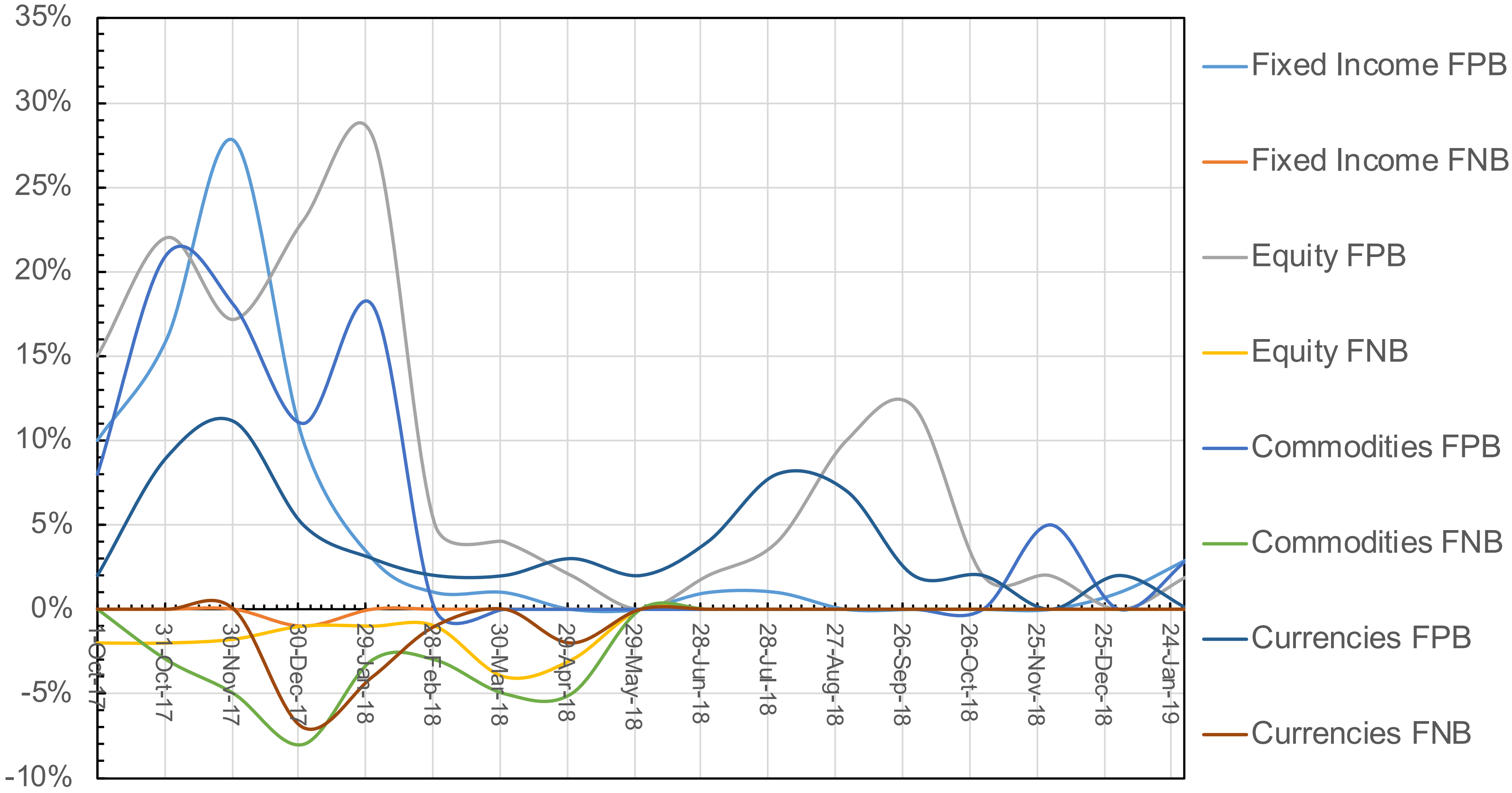
Historical evolution of the fraction of assets within an asset class that show significant bubble signals



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	3	0
	Government Bonds	55	7	0
	Finance and Insurance	21	0	0
	Corporate Bonds	79	0	0
Equity		179	2	0
	Country Indices	52	4	0
	Europe	14	0	0
	United States	113	1	0
Commodities		29	3	0
Forex		53	0	0

Throughout January, bubble activity has remained at a low level. In the following, we discuss the few bubble signals in the different sectors and evaluate some of the previous report’s predictions.

Fixed Income – Government Bond Indices

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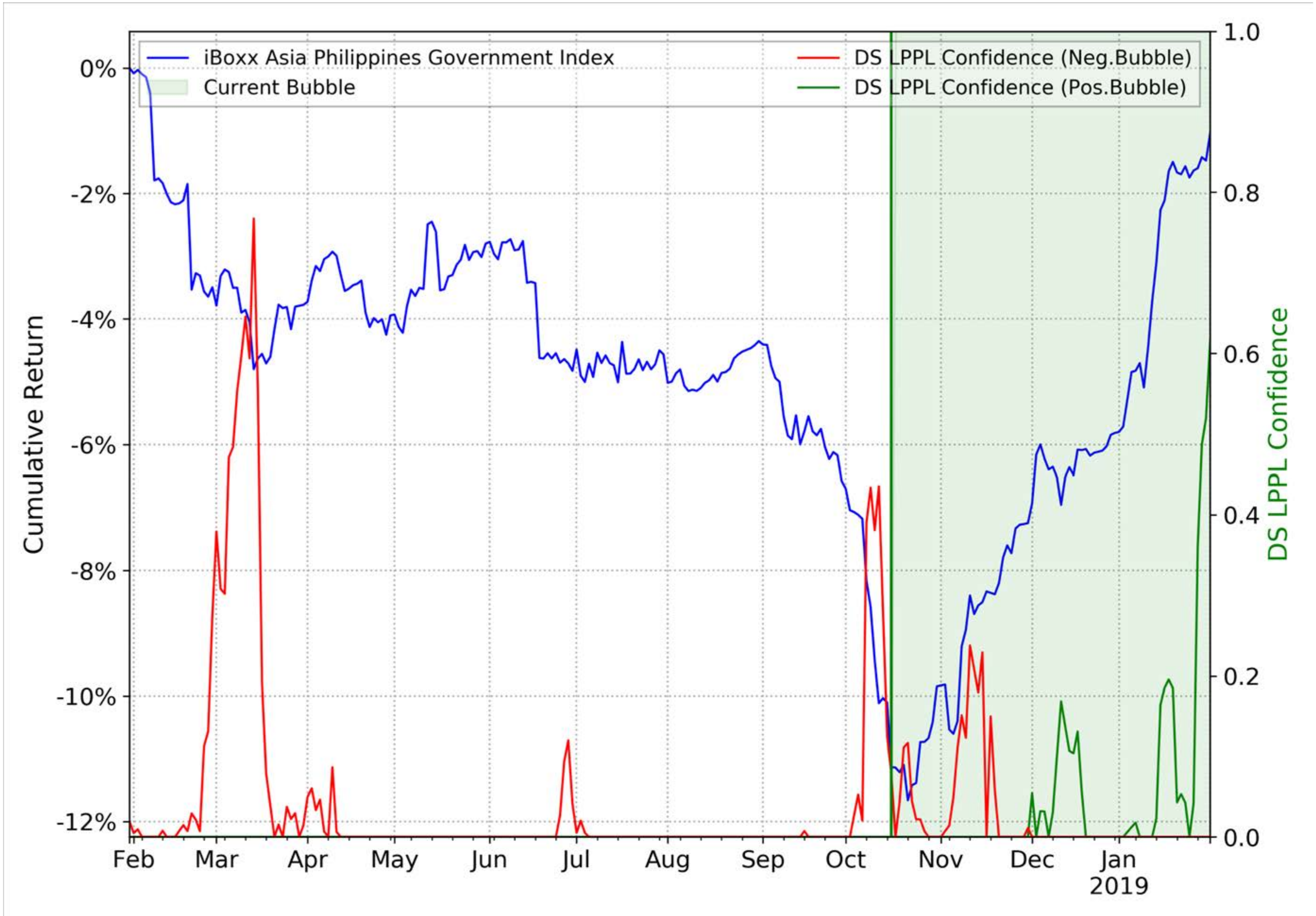
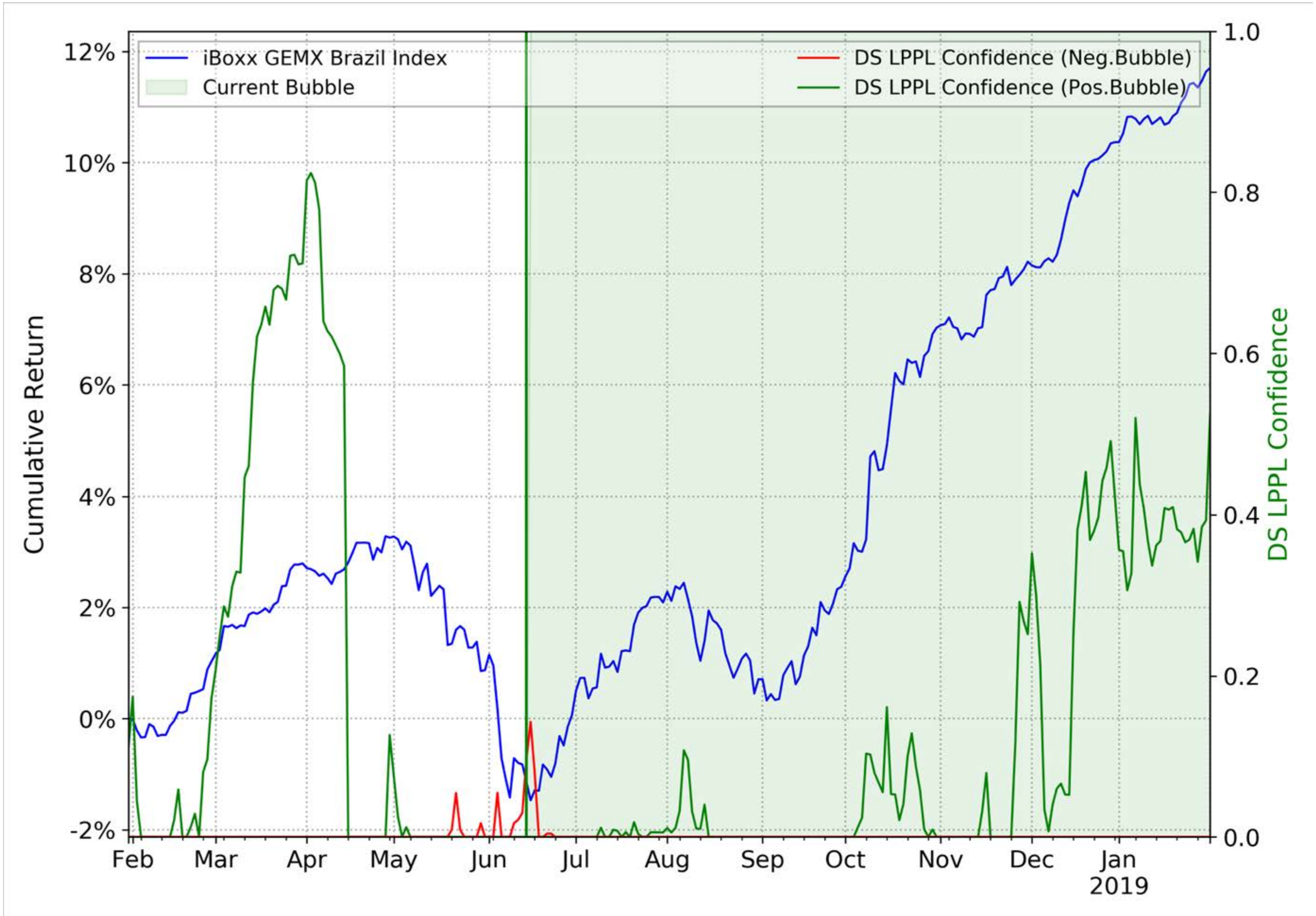
	Bubble Data					Cluster Analysis		
	Name	Bubble Size bs [%]	Duration $[days]$	DS LPPL Confidence ci [%]	Geometric Average $\sqrt{bs \cdot ci}$ [%]	Critical Time Prediction μ_{t_c}	σ_{t_c} $[days]$	Scenario Probability [%]
Positive Bubbles								
	iBoxx Asia Philippines Index	11	107	89	32	2019-02-20	3	72
	iBoxx GEMX Brazil Index	13	231	77	32	2019-02-01	1	83
	iBoxx GEMX Turkey Index	24	139	13	18	2019-01-31		85

At the top of our fixed income table, we see the Philippines Bond Index, where a medium term bubble has formed since the trough of the identified negative bubble was reached in mid October 2018, as visible on the following slide. Throughout January, the LPPLS Confidence Indicator has risen sharply to a value of 89%. Nevertheless, the index exhibits only a small calculated bubble size of about 11%.

Furthermore, the iBoxx GEMX Brazil Index has continued its surge to new heights in the past month. This continues last month's detected trend. We determine a moderate bubble size of about 13%, at a nevertheless fairly high indicator level of 79%.



iBoxx Asia Philippines Government Index
Current Bubble
DS LPPL Confidence (Neg.Bubble)
DS LPPL Confidence (Pos.Bubble)
Cumulative Return
DS LPPL Confidence
0%
-2%
-4%
-6%
-8%
-10%
-12%
1.0
0.8
0.6
0.4
0.2
0.0
Feb
Mar
Apr
May
Jun
Jul
Aug
Sep
Oct
Nov
Dec
Jan
2019

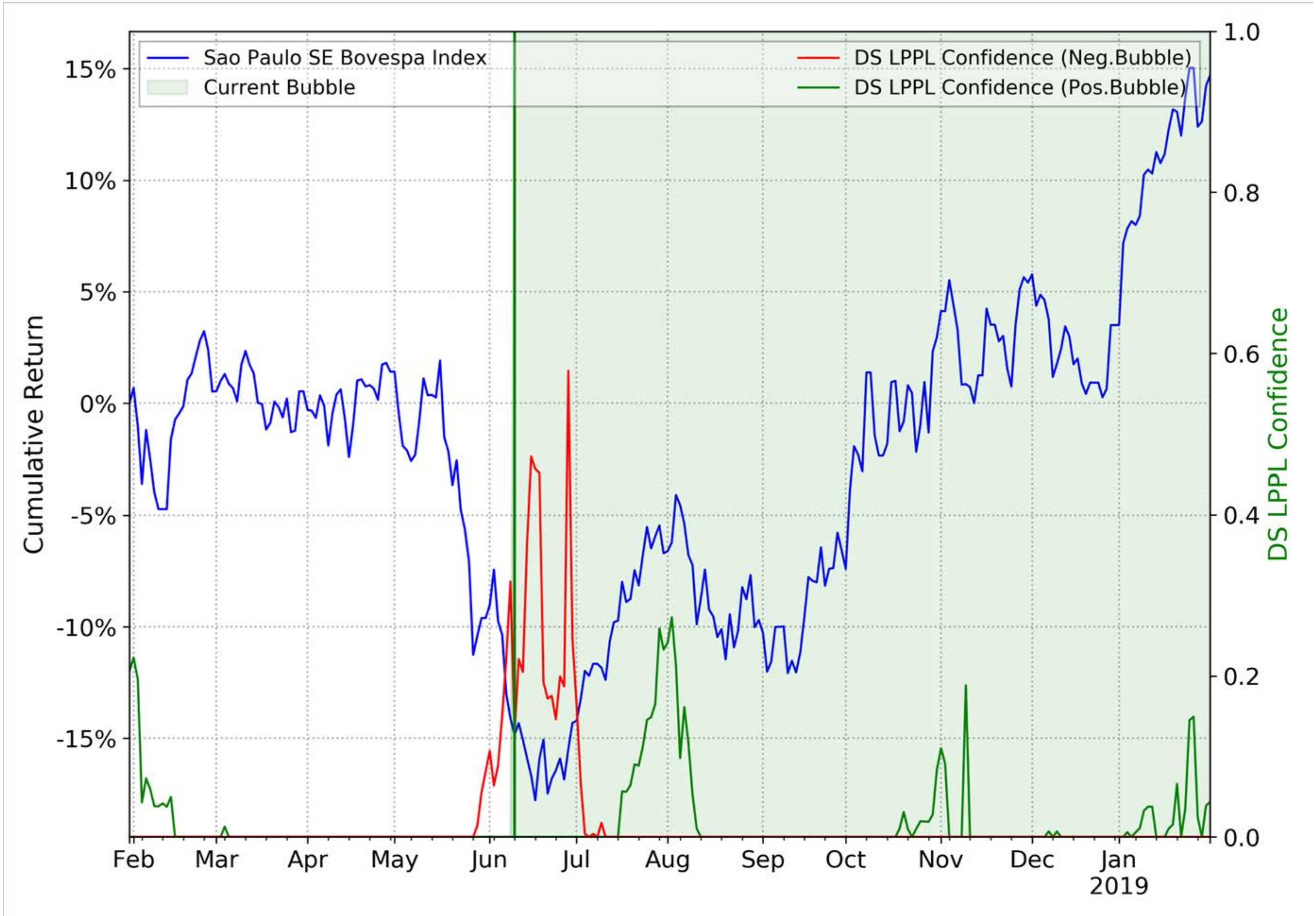

iBoxx GEMX Brazil Index
Current Bubble
DS LPPL Confidence (Neg.Bubble)
DS LPPL Confidence (Pos.Bubble)
Cumulative Return
DS LPPL Confidence
12%
10%
8%
6%
4%
2%
0%
-2%
1.0
0.8
0.6
0.4
0.2
0.0
Feb
Mar
Apr
May
Jun
Jul
Aug
Sep
Oct
Nov
Dec
Jan
2019

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_{t_c}	σ_{t_c} $[days]$	Scenario Probability [%]
Positive Bubbles								
1	Sao Paulo SE Bovespa Index	35	236	32	33	2019-02-15	15	64
2	Jakarta SE Composite Index	12	224	36	21	2019-02-15	13	65

In addition to the fixed income sector, we detect further positive bubble signals on another Brazilian Index, the Sao Paolo SE Bovespa. This finding reconfirms the formation of a growing bubble in the country's economy. The determined bubble start time also coincides with the calculated bubble start time of the bond index. This agreement of these signals is also attributable to the high positive correlation of both indices at the current time.

Secondly, we report a positive bubble signal on the Indonesian Jakarta SE Composite Index. The respective indicator series for both examples are depicted on the next slides.


Sao Paulo SE Bovespa Index
Current Bubble
DS LPPL Confidence (Neg.Bubble)
DS LPPL Confidence (Pos.Bubble)
Cumulative Return
DS LPPL Confidence
15%
10%
5%
0%
-5%
-10%
-15%
1.0
0.8
0.6
0.4
0.2
0.0
Feb
Mar
Apr
May
Jun
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Sep
Oct
Nov
Dec
Jan
2019


Jakarta SE Composite Index
Current Bubble
DS LPPL Confidence (Neg.Bubble)
DS LPPL Confidence (Pos.Bubble)
Cumulative Return
DS LPPL Confidence
2%
0%
-2%
-4%
-6%
-8%
-10%
-12%
-14%
1.0
0.8
0.6
0.4
0.2
0.0
Feb
Mar
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Jul
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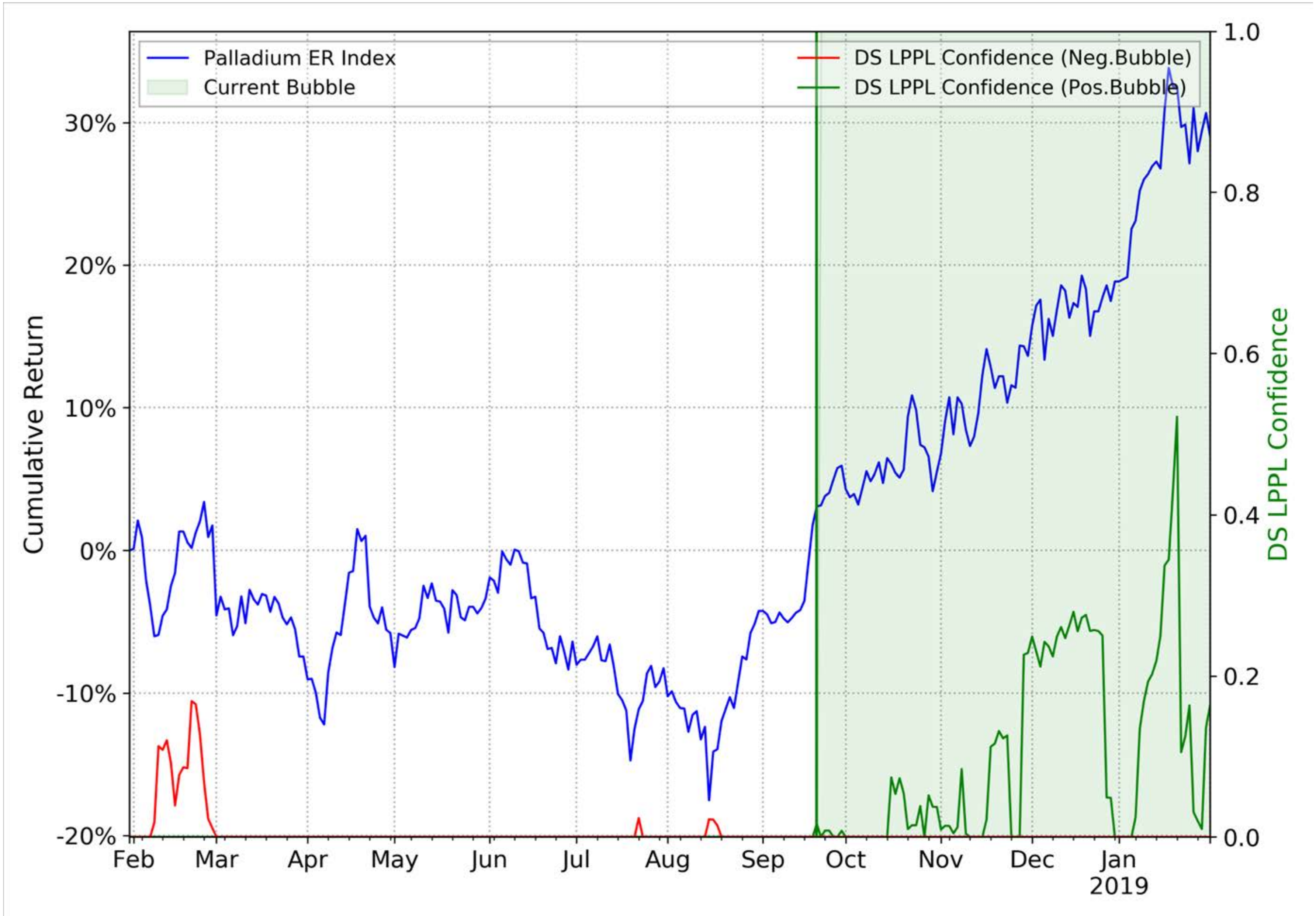
Sep
Oct
Nov
Dec
Jan
2019

Commodities

	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	Palladium ER Index	39	159	81	57	2019-03-15	3	33

Newly, we detect significant bubble growth on the Palladium Excess Return Index. The precious metal has strongly appreciated in value within the past thirty days, resulting in a bubble that has reached a size of almost 40% by now. As visible in the corresponding plot, the indicator value has progressively risen throughout this period up to a level of 81% at the current time. The average critical time of the largest parameter cluster in LPPLS fits is predicted to occur in mid March.


Palladium ER Index
Current Bubble
DS LPPL Confidence (Neg.Bubble)
DS LPPL Confidence (Pos.Bubble)
Cumulative Return
30%
20%
10%
0%
-10%
-20%
1.0
0.8
0.6
0.4
0.2
0.0
DS LPPL Confidence
Feb
Mar
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May
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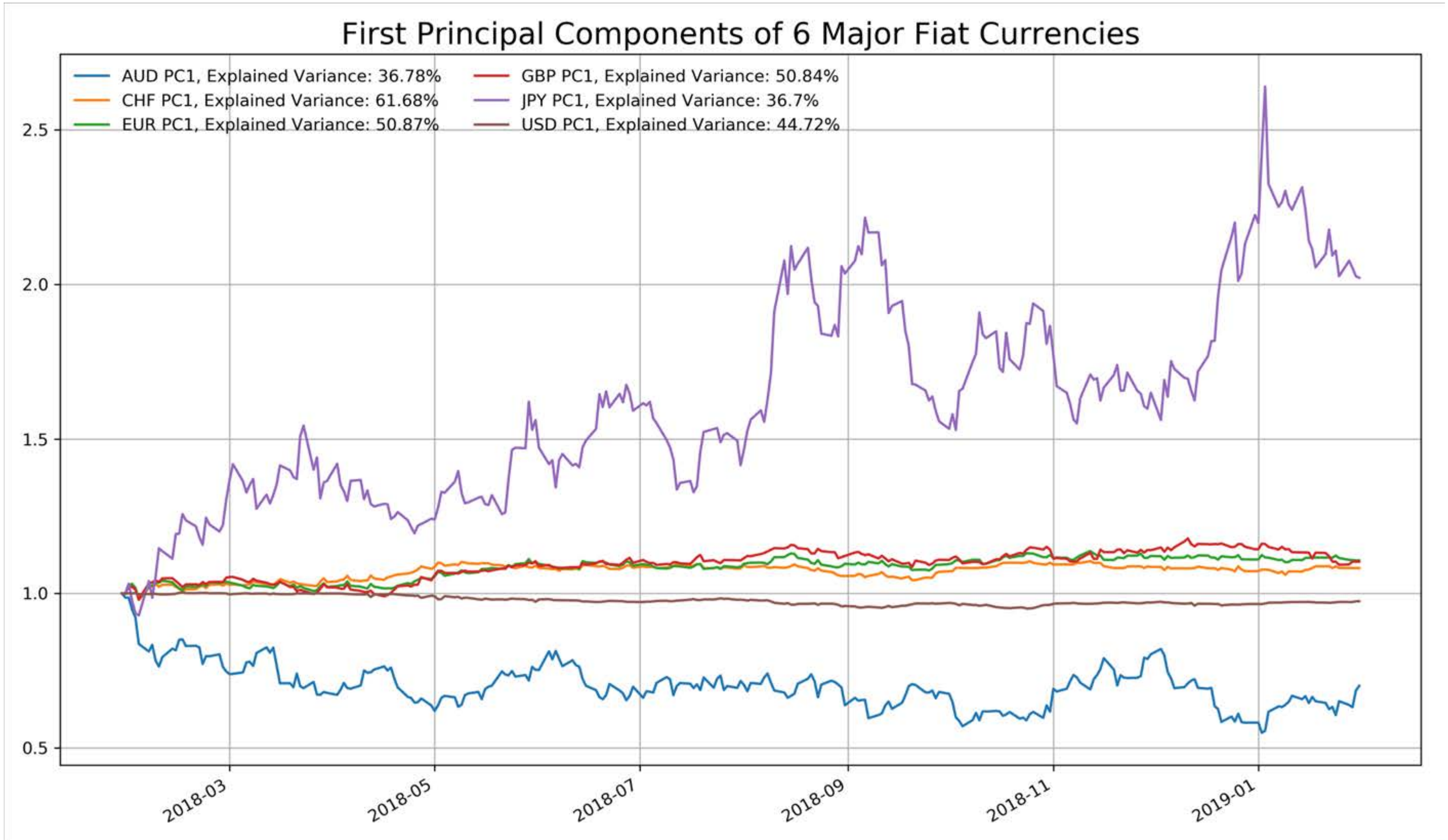
2019

Currencies – PCA



There are no relevant results to show for the forex and cryptocurrency sectors. The PCA analysis of the major currencies is shown above.

Single Stocks

For 777 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.

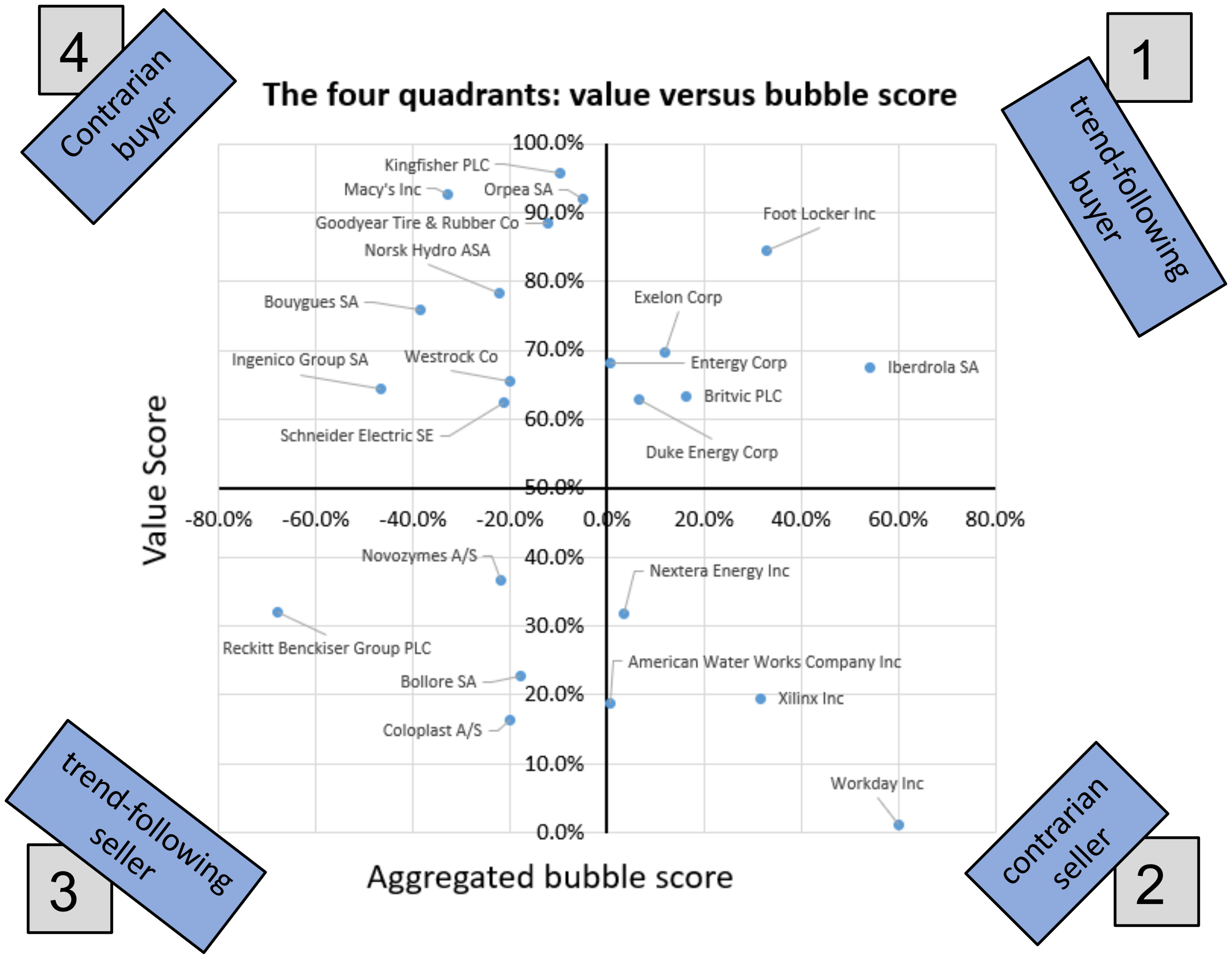
The stocks are the constituents of the Stoxx Europe 600, the S&P 500 and the Nasdaq 100 indices. From these, all doubles and stocks with incomplete data are removed. Because our financial strength indicators are specifically designed for corporates, all financial institutions are taken out of the set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

List of Indicators

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. Duke Energy Corp);
2. Quadrant 2: Stocks with a strong positive bubble score and a weak value score (e.g. Workday Inc);
3. Quadrant 3: Stocks with a strong negative bubble score and a weak value score (e.g. Bollore SA);
4. Quadrant 4: Stocks with strong negative bubble score and a strong financial strength (e.g. Orpea SA)

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%.

Single Stocks

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.

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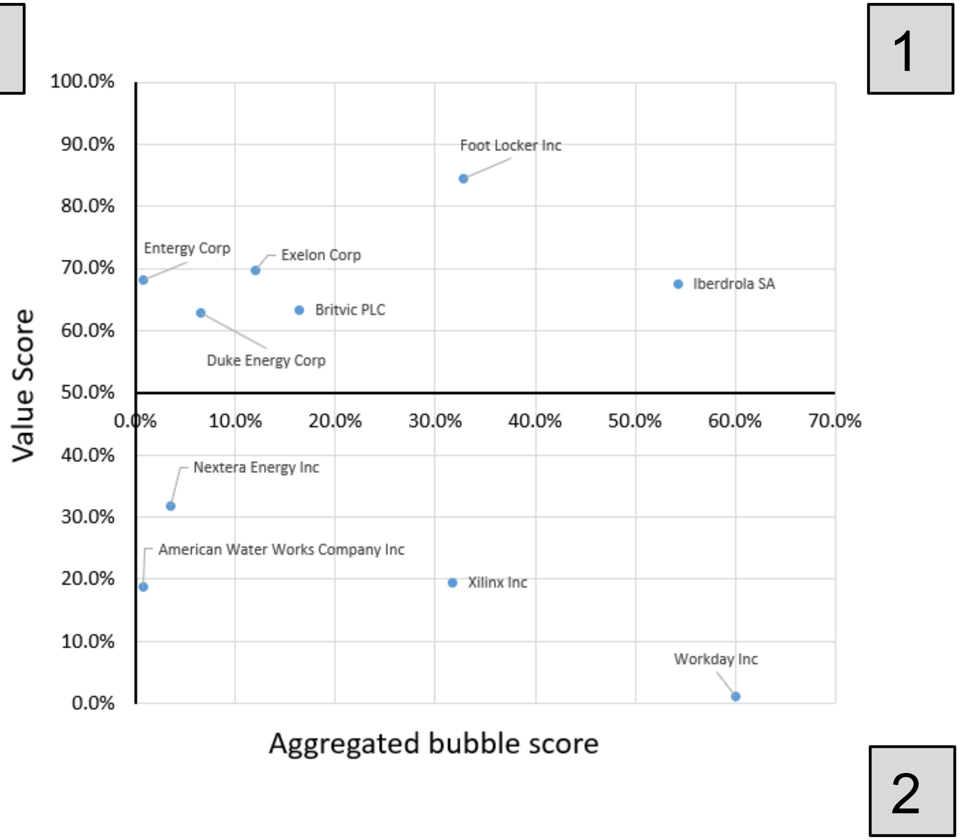
Quadrant 1 and 2 stocks

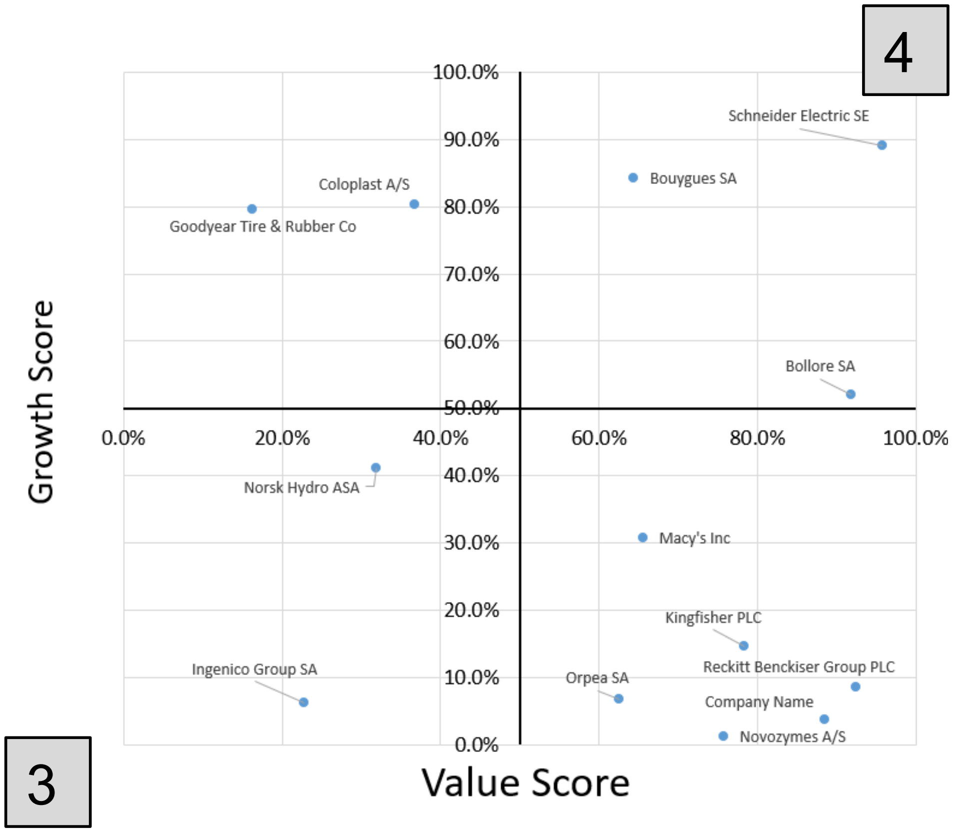
Strong positive bubble signals with strong (respectively weak) fundamentals

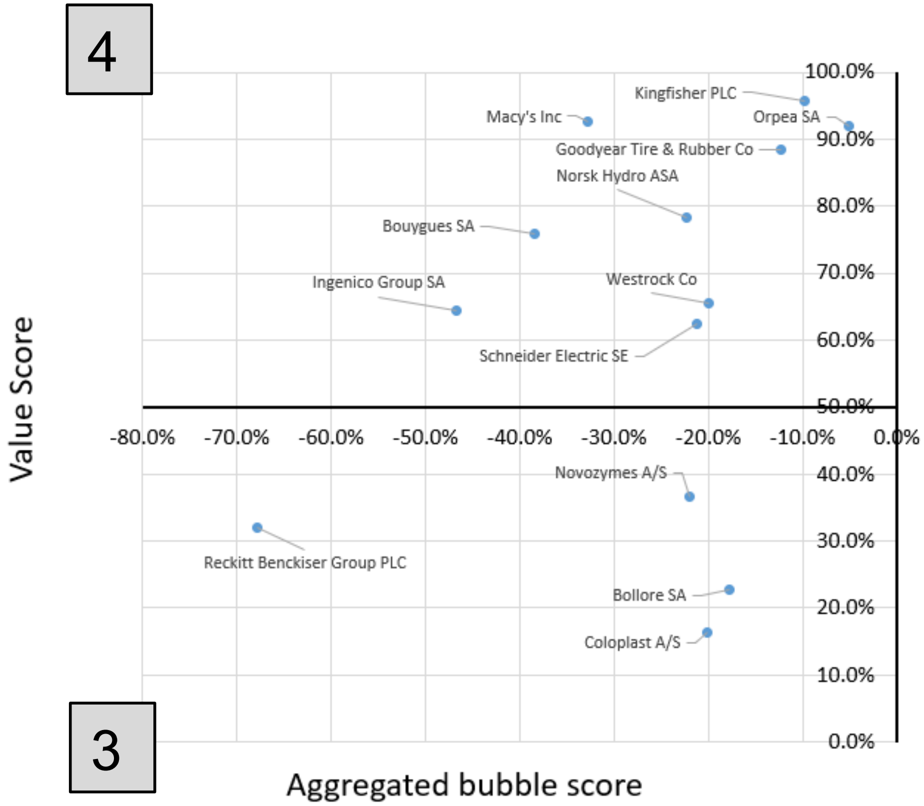


Single Stocks

Quadrant 3 and 4 stocks

Strong negative bubble signals with weak (respectively strong) fundamentals





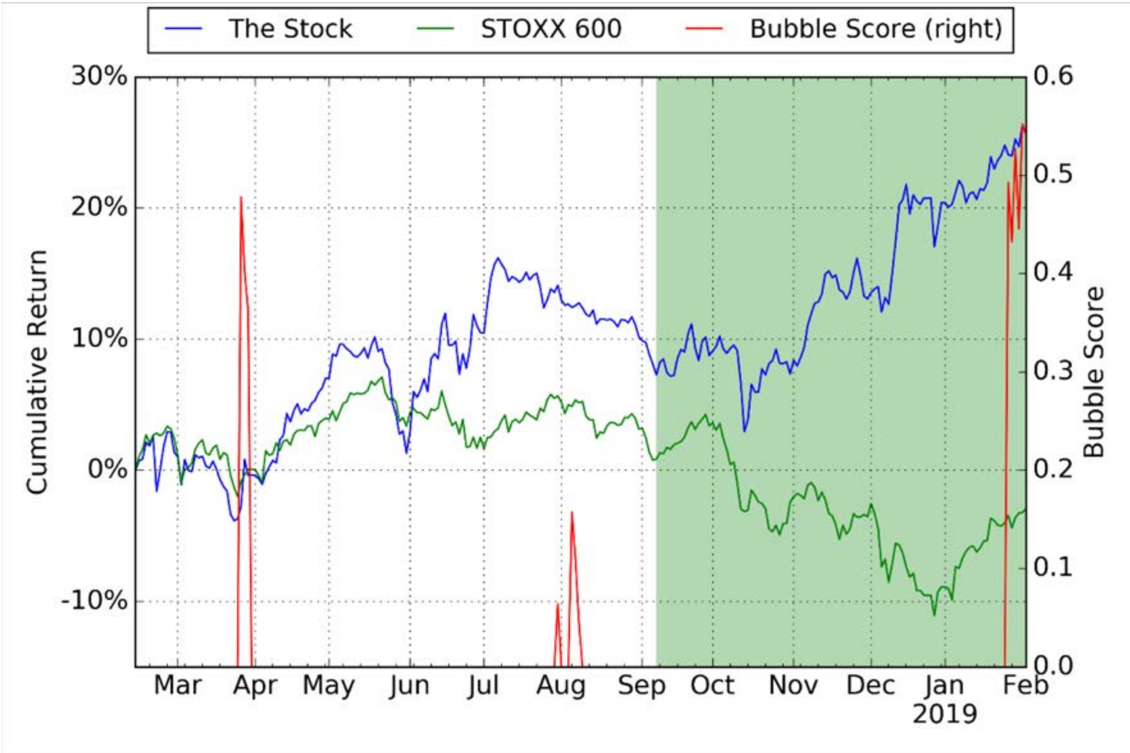
Single Stocks

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
Britvic PLC	United Kingdom	Food, Beverage & Tobacco	31.1%	20.3%	May-18	16.4%	63.4%	13.9%
Iberdrola SA	Spain	Utilities	24.6%	17.2%	Sep-18	54.3%	67.5%	29.8%
Duke Energy Corp	United States of America	Utilities	15.2%	15.2%	Feb-18	6.5%	62.8%	68.9%
Entergy Corp	United States of America	Utilities	16.4%	11.9%	May-18	0.7%	68.2%	13.0%
Exelon Corp	United States of America	Utilities	26.6%	15.6%	Jun-18	11.9%	69.7%	81.8%
Foot Locker Inc	United States of America	Retailing	11.8%	11.0%	Jul-18	32.8%	84.5%	49.5%

Single Stocks - Quadrant 1 stocks

Quadrant 1 stocks: strong positive bubble signals with strong fundamentals
Example: Iberdrola SA.

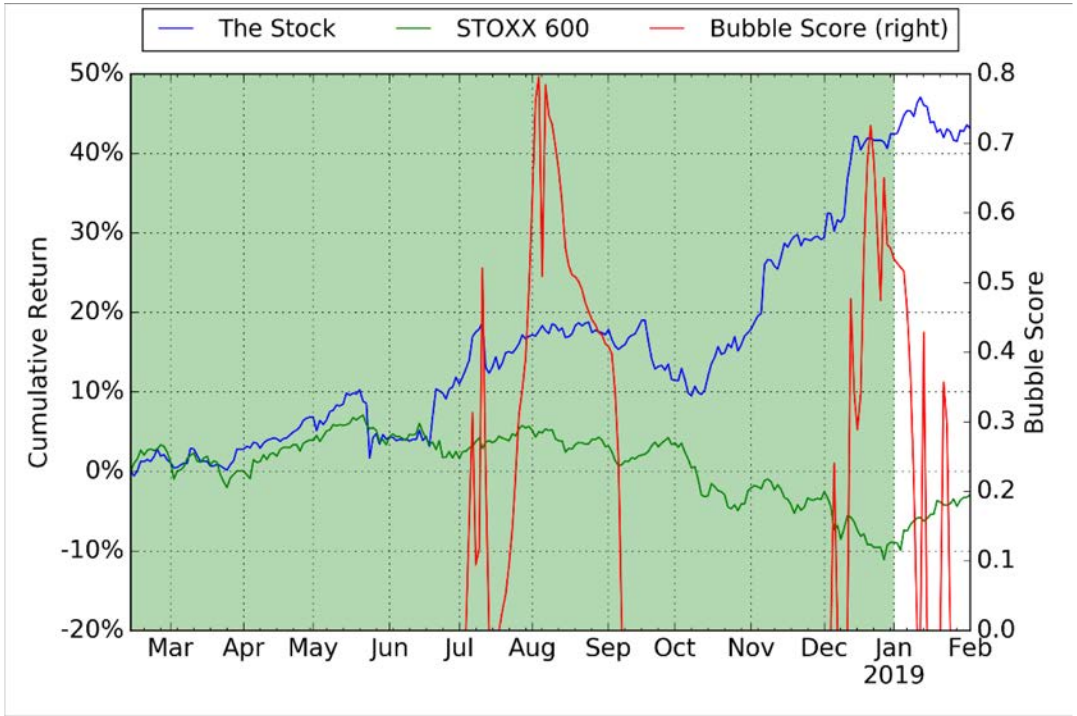


The above graph shows the one year cumulative return of the stock in blue (left hand scale), STOXX 600 in green (left hand scale) and the calculated DS LPPLS Bubble Score in red (right hand scale). The green shaded period is the strong positive bubble we identified. The Bubble Score of this seven month bubble has reached 54.3% with a bubble size 17.2%.

Single Stocks - Quadrant 1 stocks

Last month example: strong positive bubble signals with strong fundamentals, Etablissementen Franz Colruyt NV.

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 has stopped its appreciation and went into a small plateau in the past month, which is in agreement with the DS LPPLS indicator of a change of regime, but not with the strong fundamentals.



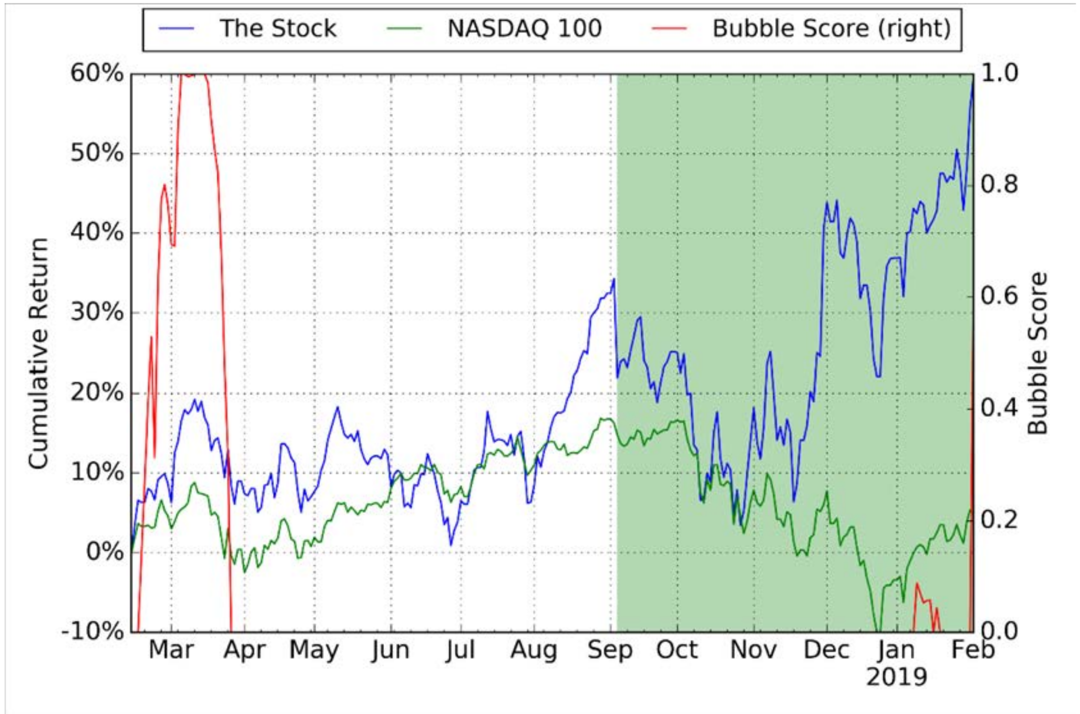
Single Stocks - Quadrant 2 stocks

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
Workday Inc	United States of America	Software & Services	49.7%	30.8%	Sep-18	60.0%	1.0%	56.3%
Xilinx Inc	United States of America	Semiconductors & Semiconductor Equipment	66.6%	64.7%	Apr-18	31.7%	19.5%	42.1%
American Water Works Company Inc	United States of America	Utilities	19.4%	14.7%	May-18	0.7%	18.7%	63.5%
Nextera Energy Inc	United States of America	Utilities	15.1%	10.2%	Mar-18	3.5%	31.8%	78.1%

Single Stocks - Quadrant 2 stocks

Quadrant 2 stocks: strong positive bubble signals with weak fundamentals
Example: Workday Inc.

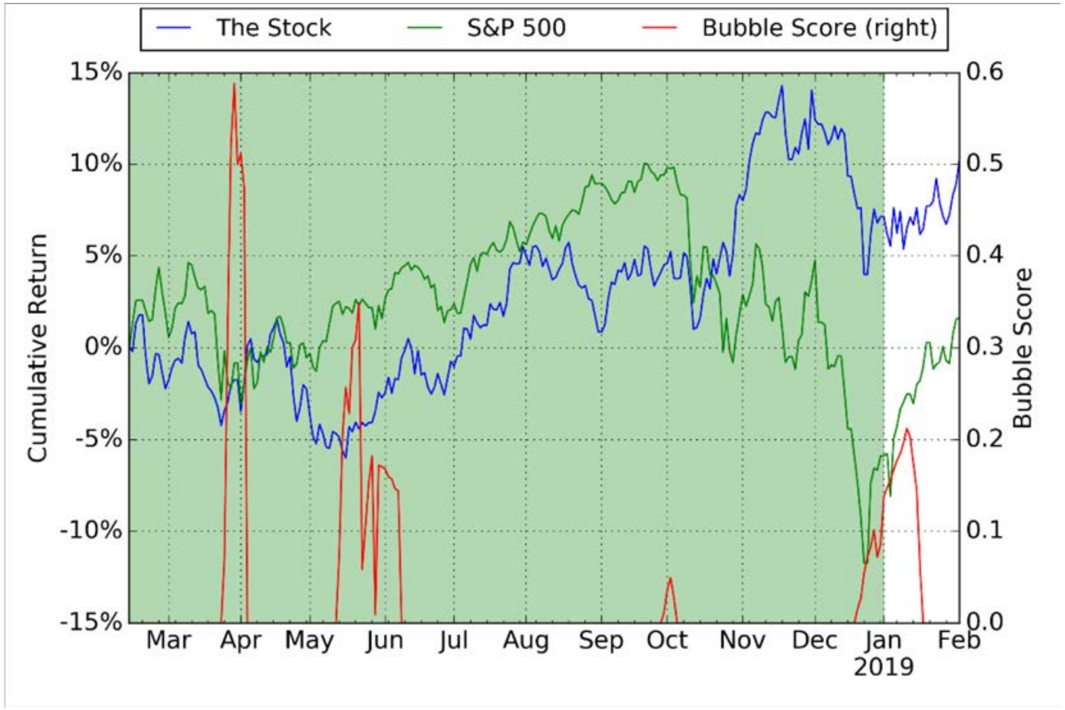


The above graph shows the one year cumulative return of the stock in blue (left hand scale), NASDAQ 100 in green (left hand scale) and the calculated DS LPPLS Bubble Score in red (right hand scale). The green shaded period is the positive bubble we identified. The Bubble Score of this five month bubble has reached 60.0% with a bubble size 30.8%. 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, Coca-Cola Co.

The figure below plots the one year cumulative return of the stock (blue), S&P 500 (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 volatile period after the peak around November, which is in agreement with the weak fundamentals and our DS LPPLS indicator.



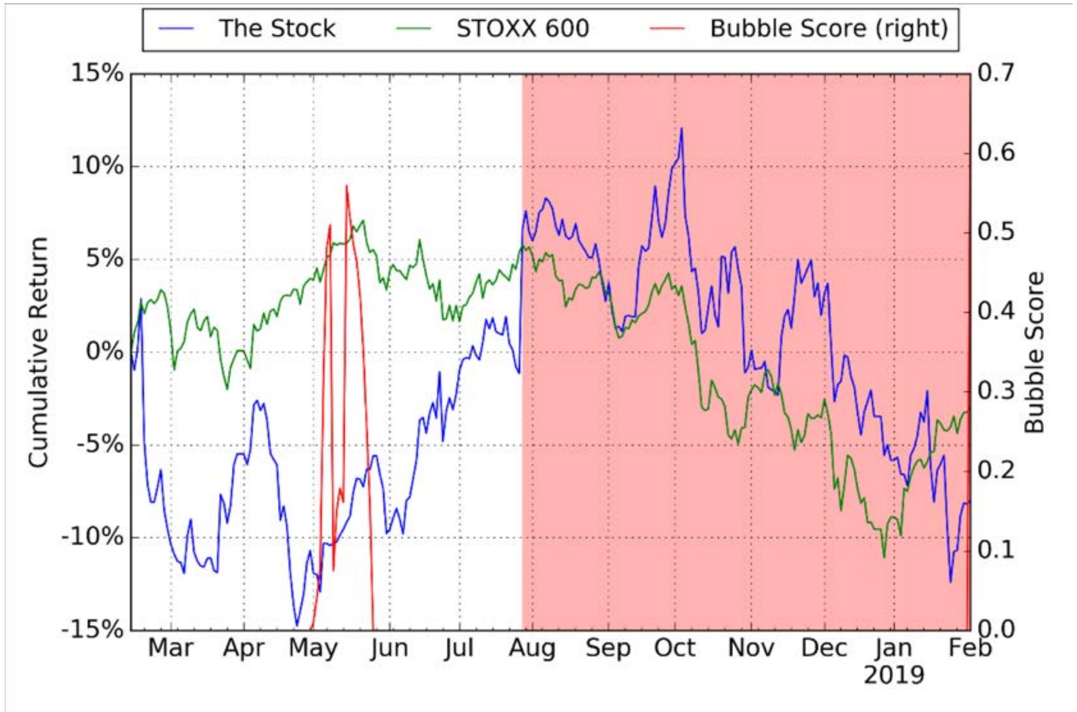
Single Stocks - Quadrant 3 stocks

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
Coloplast A/S	Denmark	Health Care Equipment & Services	17.8%	-8.0%	Jul-18	-20.1%	16.2%	79.5%
Novozymes A/S	Denmark	Materials	-11.2%	-12.3%	May-18	-22.0%	36.7%	80.3%
Bollore SA	France	Transportation	-17.5%	-17.5%	Mar-18	-17.8%	22.8%	6.3%
Reckitt Benckiser Group PLC	United Kingdom	Household & Personal Products	-8.2%	-13.7%	Jul-18	-67.8%	32.0%	41.1%

Single Stocks - Quadrant 3 stocks

Quadrant 3 stocks: strong negative bubble signals with weak fundamentals
Example: Reckitt Benckiser Group PLC.

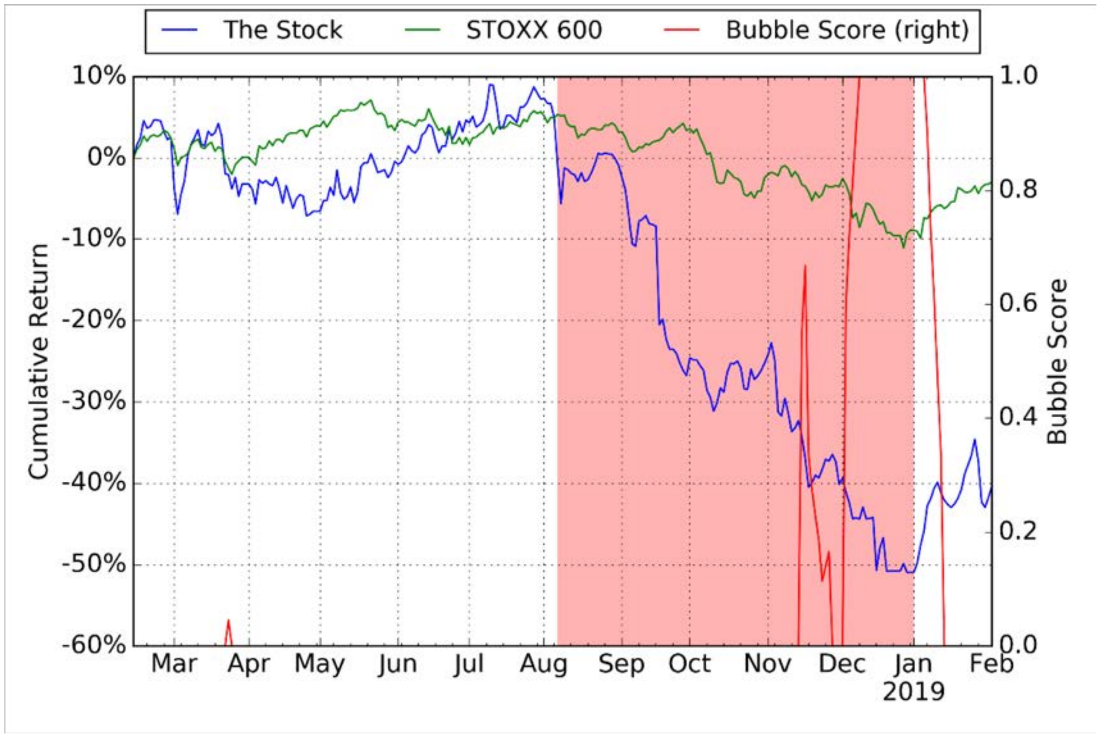


The above graph shows the one year cumulative return of the stock in blue (left hand scale), STOXX 600 in green (left hand scale) and the calculated DS LPPLS Bubble Score in red (right hand scale). The red shaded period is the negative bubble we identified. The Bubble Score of this six month bubble has reached 67.8% with a bubble size -13.7%.

Single Stocks - Quadrant 3 stocks

Last month example: strong negative bubble signals with weak fundamentals, Zalando SE.

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 quite strong rebound in the past month, which is in agreement with the DS LPPLS indicator. Given the weak fundamentals, we can expect an increased volatility in the coming months.



Single Stocks - Quadrant 4 stocks

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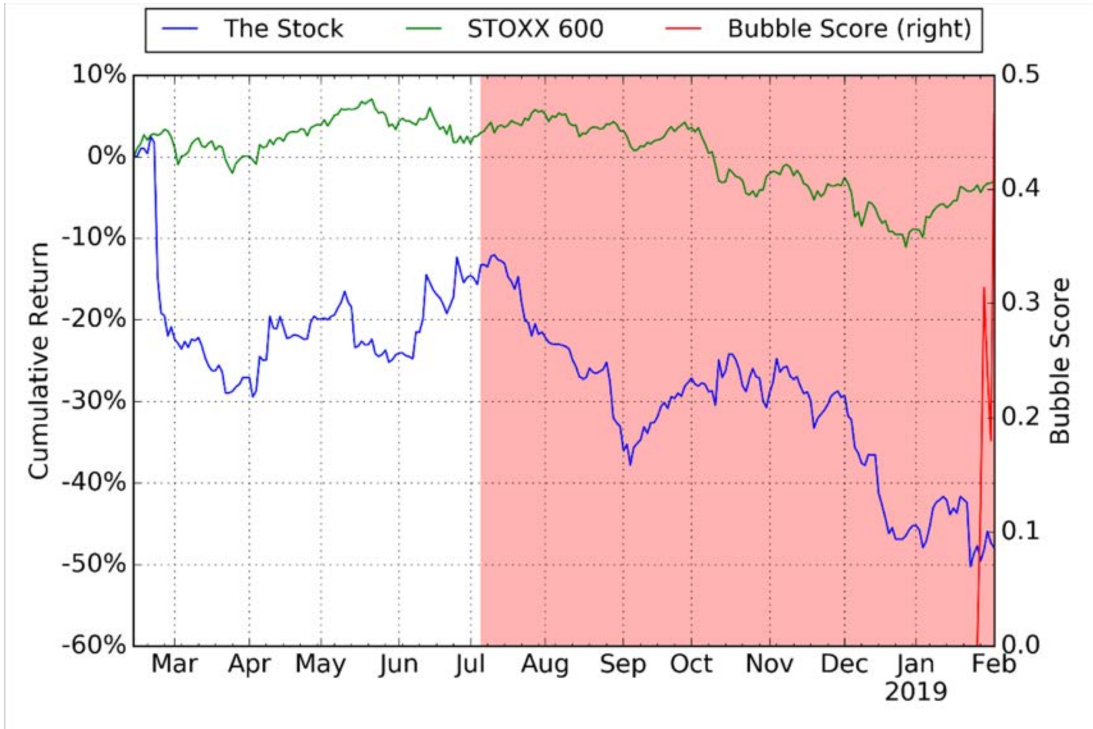
Quadrant 4 stocks: strong negative bubble signals with strong fundamentals

Company Name	Country of Headquarters	GICS Industry Group Name	Yearly Return	Bubble Size	Bubble Start	Bubble Score	Value Score	Growth Score
Goodyear Tire & Rubber Co	United States of America	Automobiles & Components	-29.8%	-25.4%	Mar-18	-12.3%	88.5%	3.7%
Bouygues SA	France	Capital Goods	-25.3%	-26.5%	May-18	-38.4%	75.8%	1.3%
Ingenico Group SA	France	Technology Hardware & Equipment	-48.4%	-39.9%	Jul-18	-46.7%	64.4%	84.3%
Orpea SA	France	Health Care Equipment & Services	-15.6%	-29.9%	Jul-18	-5.1%	91.9%	51.9%
Schneider Electric SE	France	Capital Goods	-12.2%	-13.7%	Apr-18	-21.2%	62.5%	6.7%
Kingfisher PLC	United Kingdom	Retailing	-37.3%	-24.2%	May-18	-9.8%	95.7%	89.0%
Norsk Hydro ASA	Norway	Materials	-30.9%	-20.7%	Apr-18	-22.3%	78.4%	14.6%
Macy's Inc	United States of America	Retailing	-2.8%	-27.6%	Jun-18	-32.8%	92.5%	8.5%
Westrock Co	United States of America	Materials	-40.4%	-36.5%	Jun-18	-19.9%	65.6%	30.7%

Single Stocks - Quadrant 4 stocks

Quadrant 4 stocks: strong negative bubble signals with strong fundamentals
Example: Ingenico Group SA.

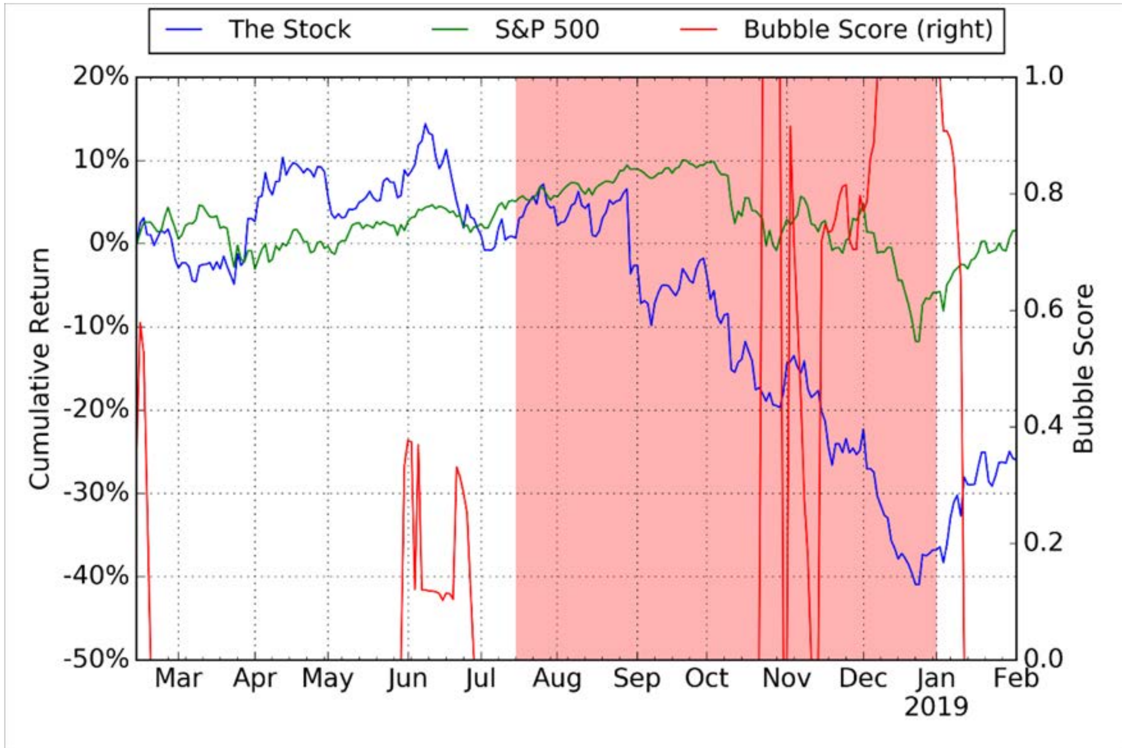


The above graph shows the one year cumulative return of the stock in blue (left hand scale), STOXX 600 in green (left hand scale) and the calculated DS LPPLS Bubble Score in red (right hand scale). The red shaded period is the strong negative bubble we identified. The Bubble Score of this seven month bubble has reached 46.7% with a bubble size -39.9%. 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, PVH Corp.

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 started a strong rebound in the past month. We expect this stock to appreciate in the future due to the strong fundamentals and following its neglect by investors in previous months.



Sectors

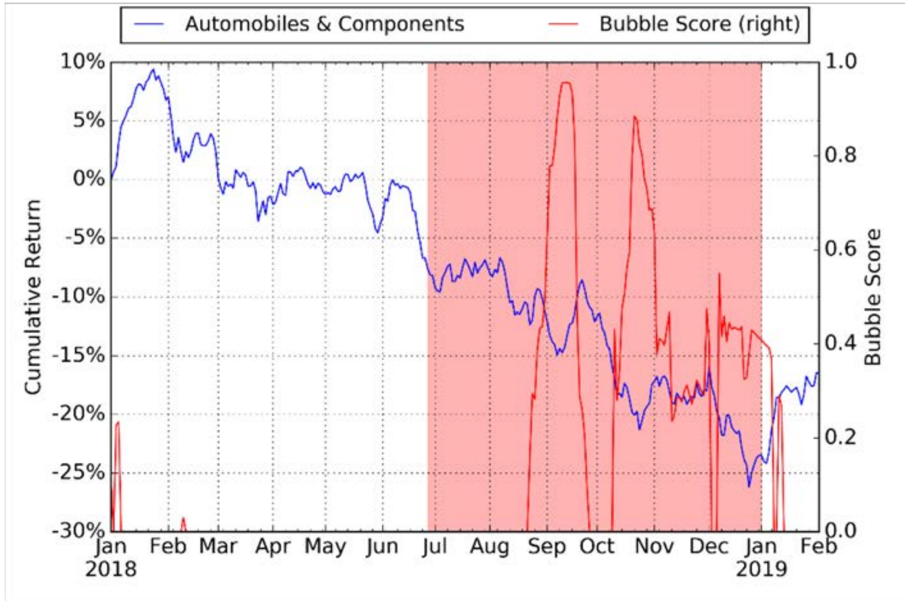
GICS Industry Group Name	Yearly Return		Bubble Size		Bubble Score		Value Score		Growth Score	
	Feb 1st	Jan 1st	Feb 1st	Jan 1st	Feb 1st	Jan 1st	Feb 1st	Jan 1st	Feb 1st	Jan 1st
Pharmaceuticals, Biotechnology & Life Sciences	2.9%	-4.6%	0.0%	0.0%	0.0%	0.0%	66.2%	63.9%	49.0%	57.8%
Consumer Services	-3.0%	-11.2%	0.0%	0.0%	0.0%	0.0%	31.5%	30.6%	48.4%	49.4%
Retailing	3.5%	0.1%	0.0%	-15.9%	0.0%	-50.7%	18.4%	19.2%	58.5%	59.5%
Transportation	-2.3%	-16.4%	0.0%	0.0%	0.0%	0.0%	62.4%	56.5%	49.7%	55.7%
Consumer Durables & Apparel	-6.2%	-15.3%	0.0%	-18.1%	0.0%	-40.5%	37.0%	36.9%	59.4%	57.5%
Semiconductors & Semiconductor Equipment	-9.9%	-17.3%	0.0%	0.0%	0.0%	0.0%	62.2%	56.8%	30.3%	28.8%
Technology Hardware & Equipment	-3.9%	-11.6%	0.0%	0.0%	0.0%	0.0%	74.1%	73.4%	41.9%	40.3%
Automobiles & Components	-19.2%	-28.2%	0.0%	-17.4%	0.0%	-41.9%	77.6%	75.8%	52.9%	48.7%
Telecommunication Services	-8.2%	-12.6%	0.0%	0.0%	0.0%	0.0%	66.1%	62.3%	35.6%	39.6%
Energy	-3.6%	-22.4%	0.0%	-22.5%	0.0%	-69.4%	53.2%	51.5%	46.4%	54.9%
Software & Services	2.9%	-4.5%	0.0%	0.0%	0.0%	0.0%	39.6%	38.8%	47.5%	46.5%
Materials	-13.1%	-22.8%	0.0%	-16.8%	0.0%	-36.6%	53.1%	53.1%	43.3%	42.1%
Health Care Equipment & Services	8.8%	-0.3%	0.0%	0.0%	0.0%	0.0%	68.5%	66.5%	59.1%	58.6%
Capital Goods	-12.5%	-22.8%	0.0%	-15.1%	0.0%	-50.5%	47.9%	47.8%	51.0%	53.1%
Media & Entertainment	3.6%	-8.2%	0.0%	0.0%	0.0%	0.0%	30.7%	27.0%	52.6%	51.5%
Commercial & Professional Services	3.8%	-8.5%	0.0%	0.0%	0.0%	0.0%	34.5%	34.0%	51.2%	48.6%
Food & Staples Retailing	1.1%	-4.8%	0.0%	0.0%	0.0%	0.0%	52.2%	54.1%	64.3%	63.0%
Household & Personal Products	1.8%	-3.6%	0.0%	0.0%	0.0%	0.0%	37.3%	36.9%	50.5%	51.8%
Food, Beverage & Tobacco	-9.6%	-17.8%	0.0%	0.0%	0.0%	0.0%	45.8%	44.5%	59.1%	57.4%
Utilities	9.5%	0.7%	0.0%	0.0%	0.0%	0.0%	53.3%	52.0%	44.7%	46.8%
Insurance	-7.4%	-16.3%	0.0%	-14.2%	0.0%	-51.4%	-	-	-	-
Real Estate	6.1%	-7.4%	0.0%	0.0%	0.0%	0.0%	-	-	-	-
Diversified Financials	-12.3%	-20.5%	0.0%	-15.3%	0.0%	-39.8%	-	-	-	-
Banks	-19.0%	-26.1%	0.0%	-17.5%	0.0%	-19.4%	-	-	-	-

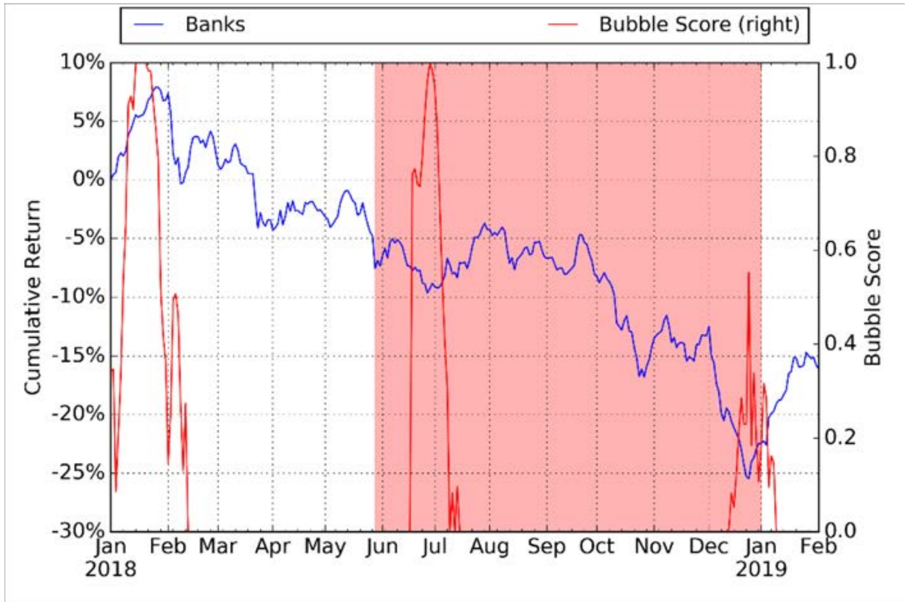
Sectors

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.

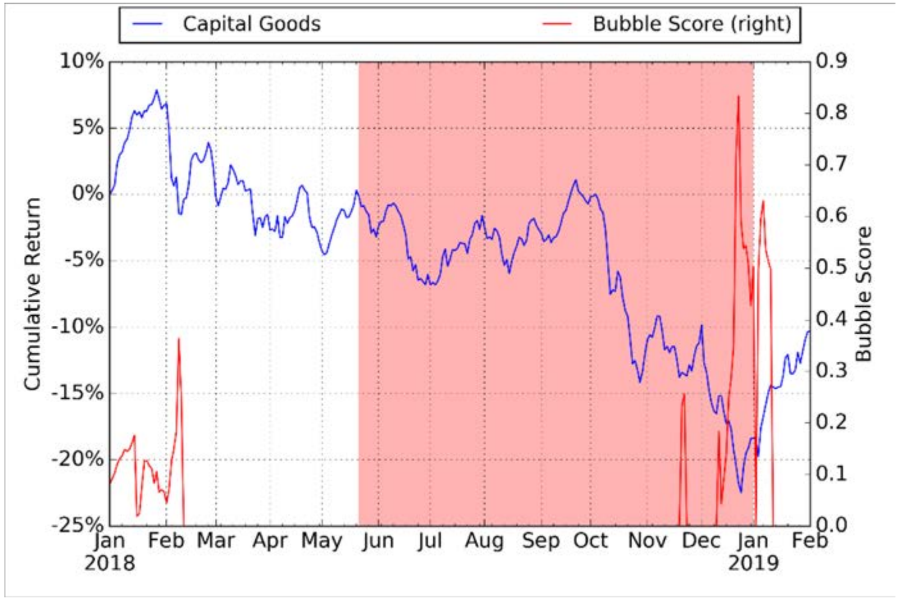
This month, we do not find any industry group has a significant bubble score.

The price evolutions following the negative bubble we identified last month in the 9 industry groups are presented below and in the next two slides.





Sectors


Capital Goods
Bubble Score (right)
Cumulative Return
Bubble Score
10%
5%
0%
-5%
-10%
-15%
-20%
-25%
0.9
0.8
0.7
0.6
0.5
0.4
0.3
0.2
0.1
0.0
Jan 2018
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Apr
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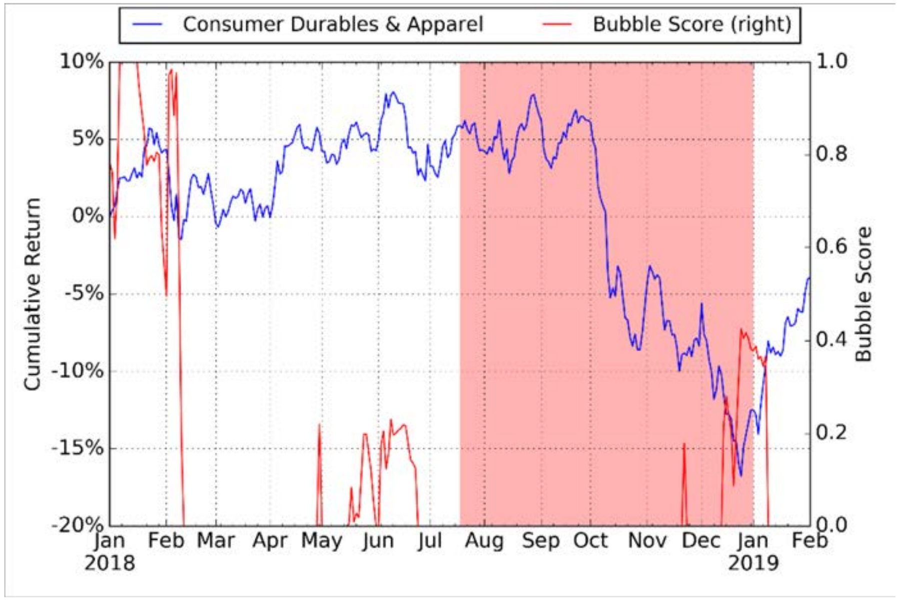
Oct
Nov
Dec
Jan 2019
Feb


Consumer Durables & Apparel
Bubble Score (right)
Cumulative Return
Bubble Score
10%
5%
0%
-5%
-10%
-15%
-20%
1.0
0.8
0.6
0.4
0.2
0.0
Jan 2018
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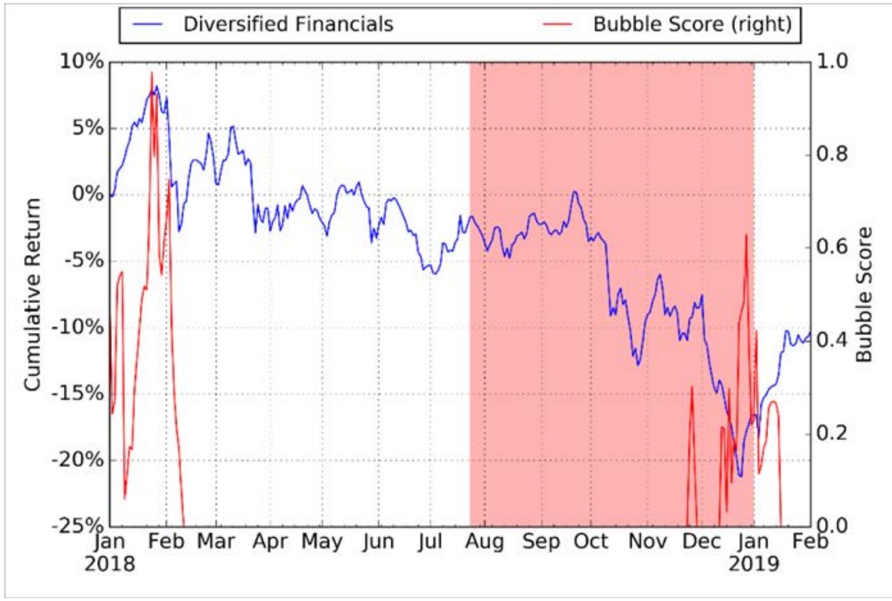
Diversified Financials
Bubble Score (right)
Cumulative Return
Bubble Score
10%
5%
0%
-5%
-10%
-15%
-20%
-25%
1.0
0.8
0.6
0.4
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Jan 2018
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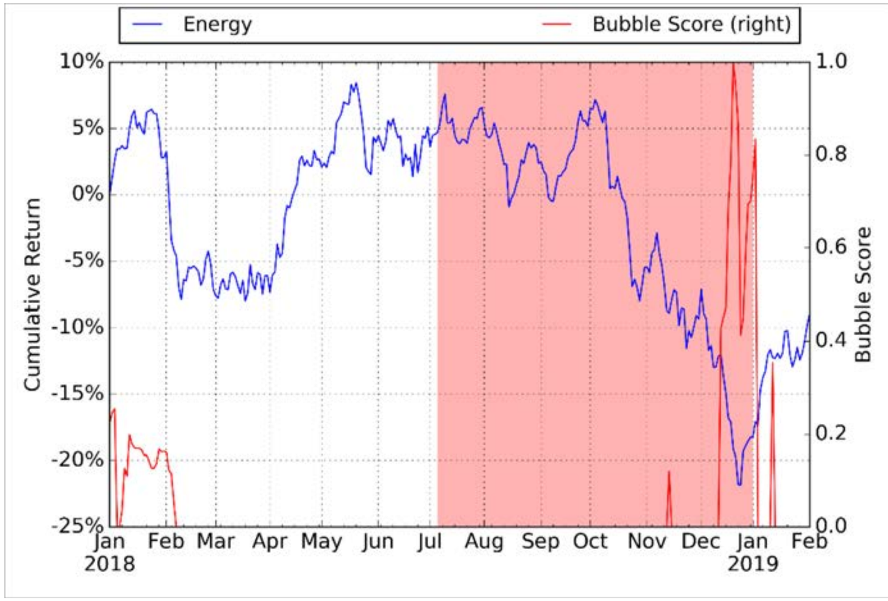
Energy
Bubble Score (right)
Cumulative Return
Bubble Score
10%
5%
0%
-5%
-10%
-15%
-20%
-25%
1.0
0.8
0.6
0.4
0.2
0.0
Jan 2018
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Entrepreneurial Risks
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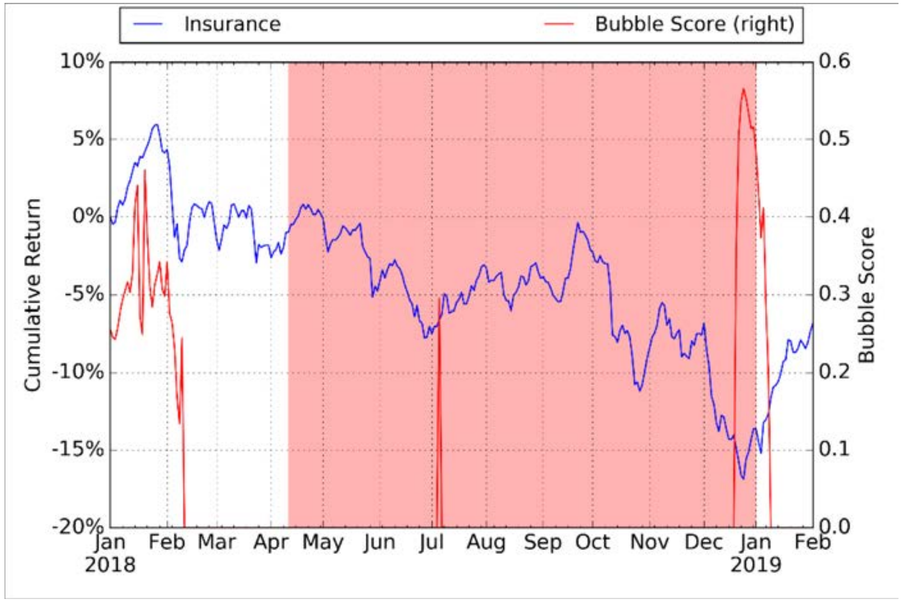
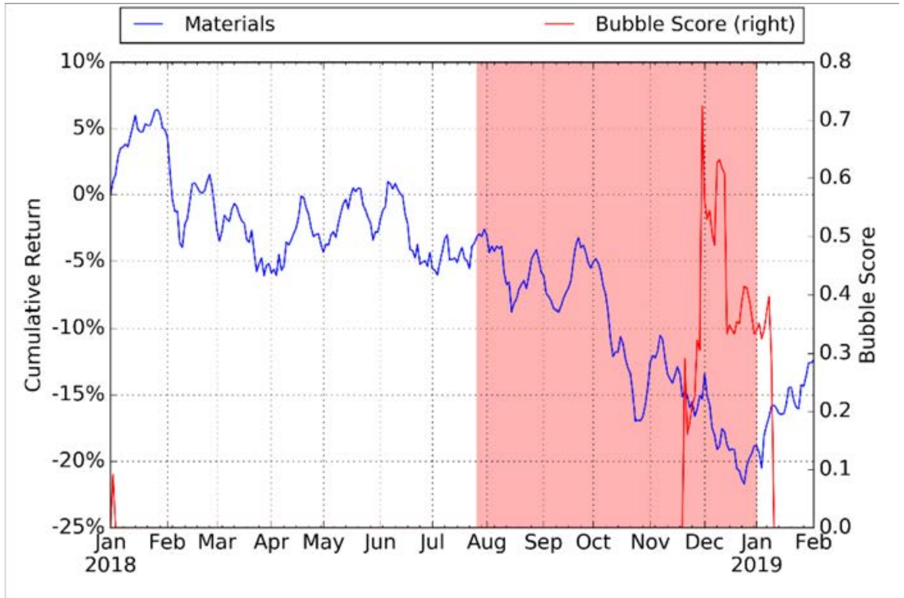
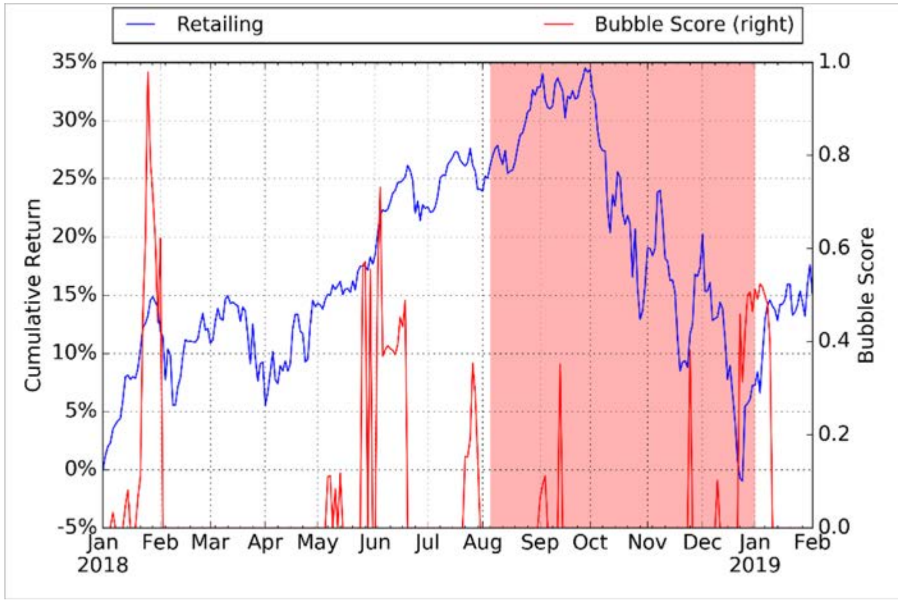






Portfolio Construction & Performance

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.

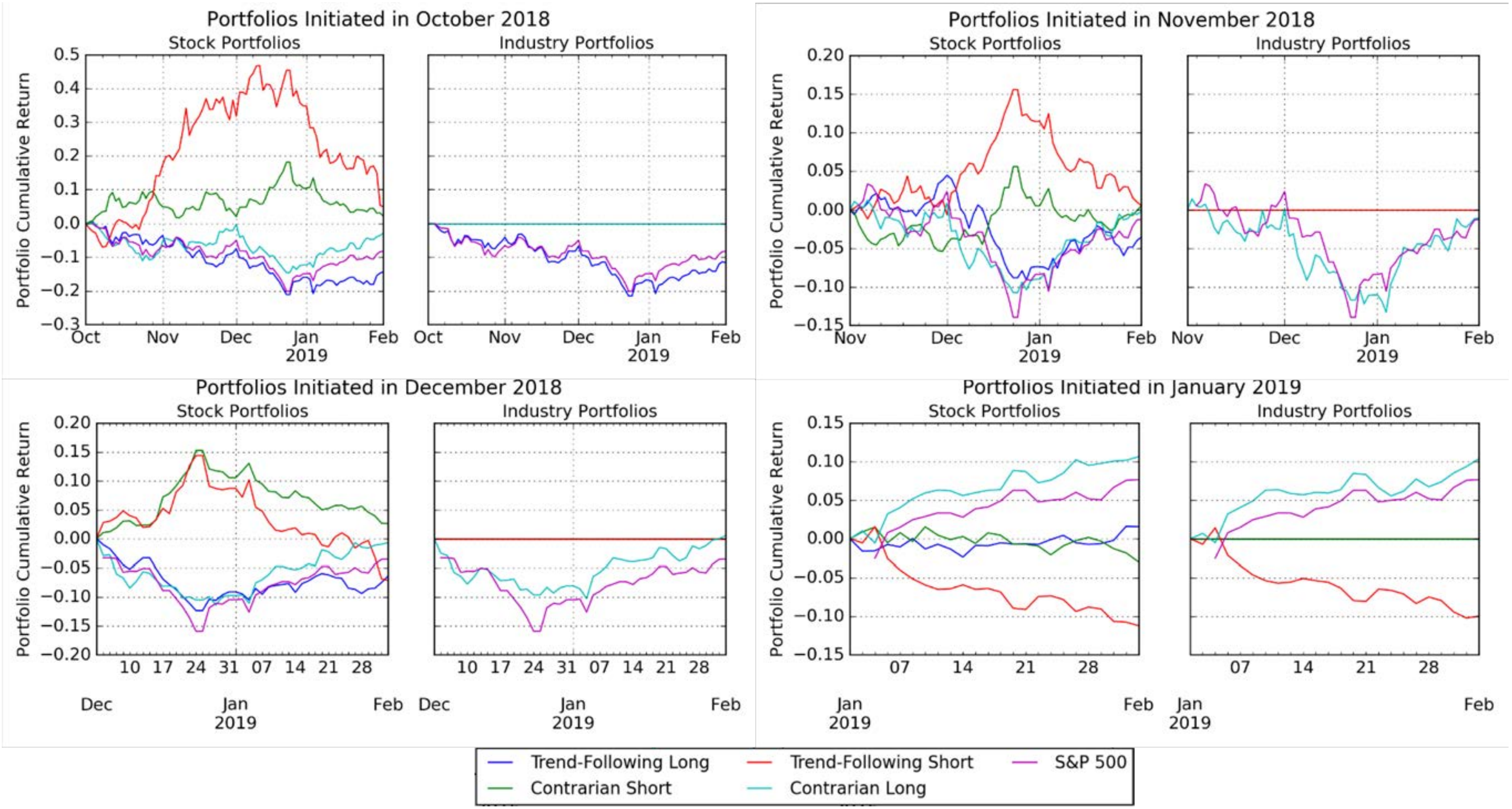
Portfolio Construction & Performance

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 Long Portfolios started to perform better due to the market appreciations in the past month, 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.

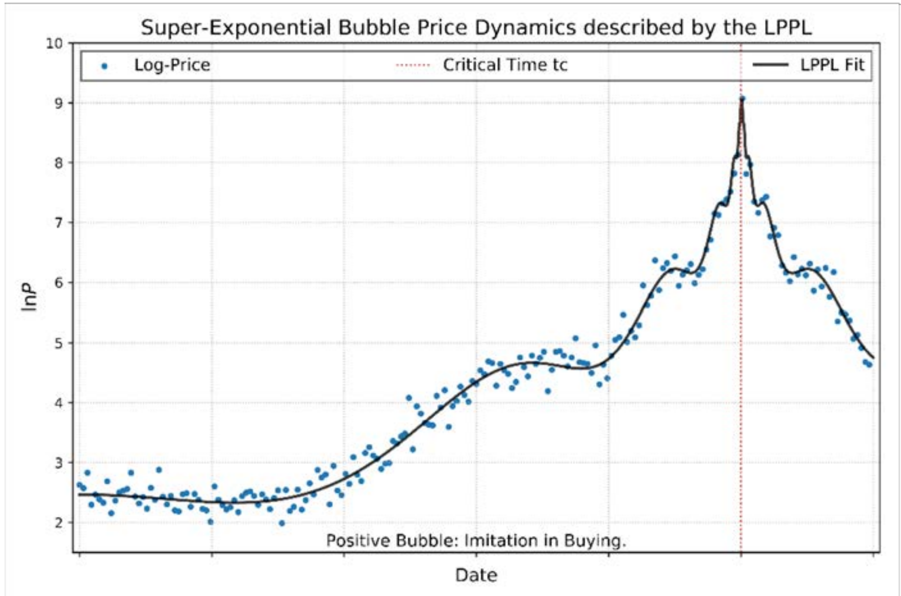
Appendix

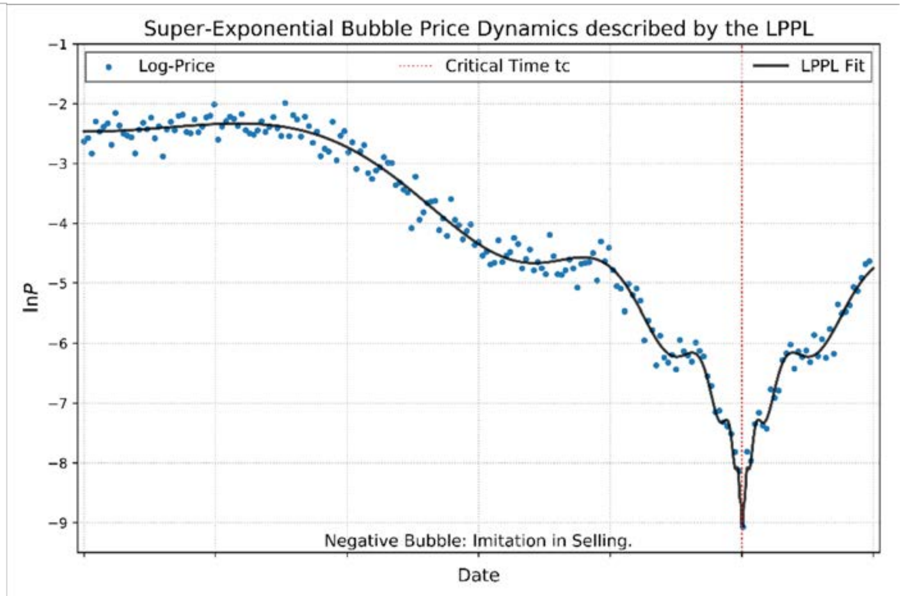
Methodology

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:

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

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

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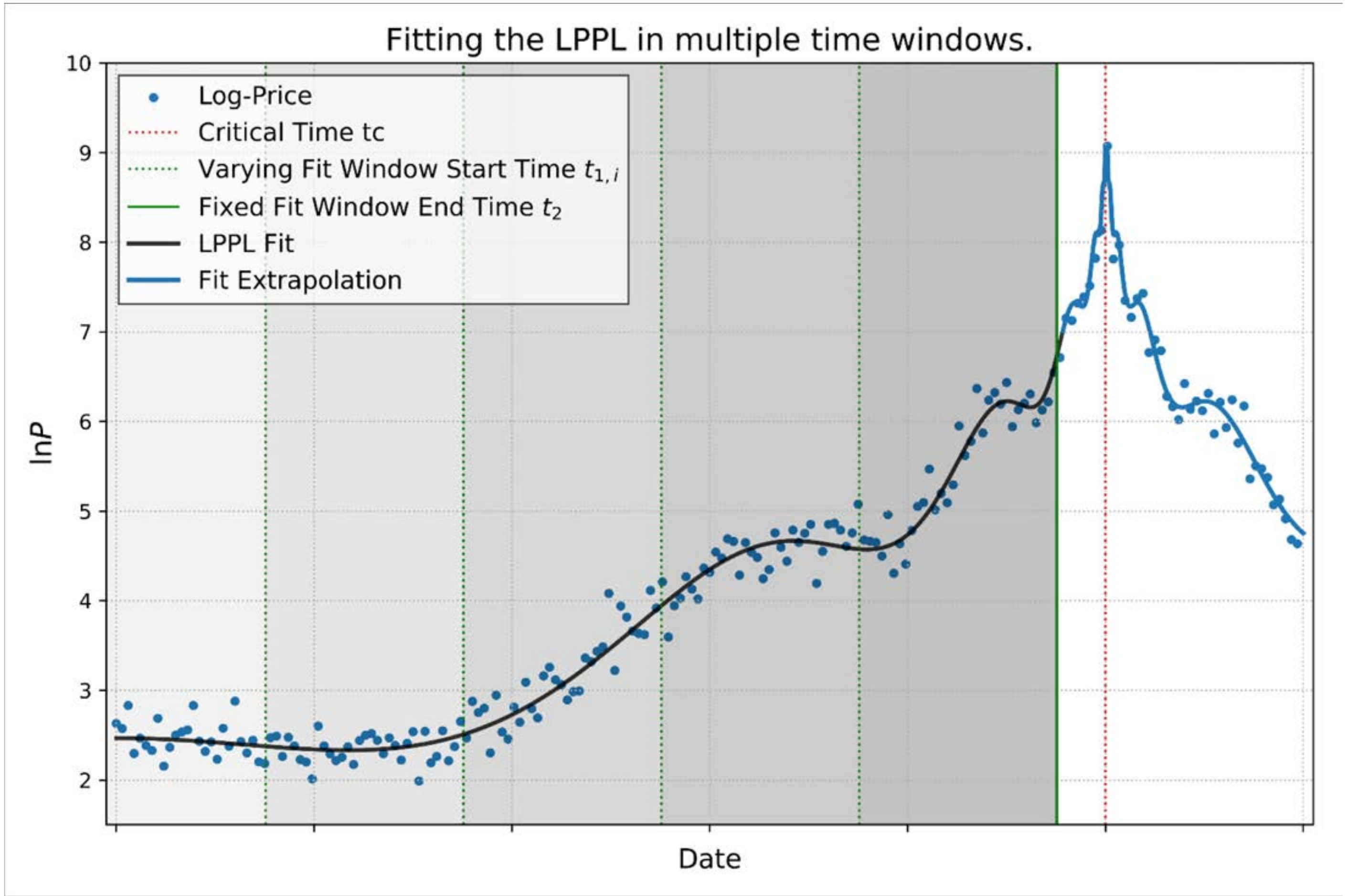


In order to avoid overfitting and to continuously collect information about price dynamics, we scan asset log-price trajectories for super-exponential price dynamics by sequentially fitting the LPPLS model in different time windows to the underlying price series. The procedure is illustrated in the plot.

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 economiques 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.

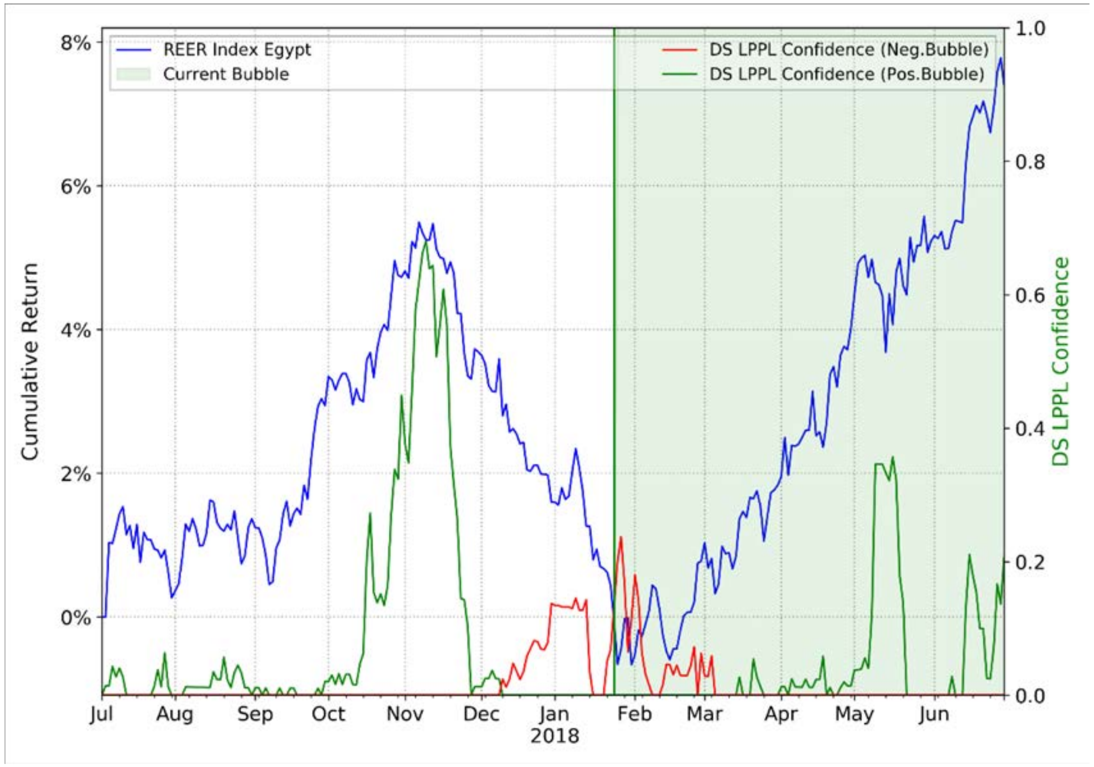
The first section provides asset and estimated bubble characteristics (size and duration), as well as the value of the confidence indicator. We rank assets according to their geometric average of the absolute of bubble size and confidence indicator. In this way, we incorporate the bubble size into the 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_{t_c}	σ_{t_c} $[days]$	**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.

Value and Growth Score

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).

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