The FCO Cockpit
Global Bubble Status Report

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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

Announcement

kmeans Clustering for Critical Time Prediction:

Following the methodology established in a recent paper by Gerlach, Demos and Sornette [1], we employ kmeans 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 parameter 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 to occur in the price of an asset.

As we fit the LPPLS model on many differently time window sizes, we often encounter variation in the LPPLS parameters obtained from each fit. The higher the similarity of the resulting parameters for different window sizes, the more we trust their prediction for the critical time parameter. This idea of enhanced trust in the results when they repetitively occur on multiple time scales is also the foundation of the LPPLS Confidence Indicator [2].

We detect similar LPPLS fits by applying kmeans clustering to the set of parameters fitted for different time windows. In this report, for the first time, we report the mean critical time μ_{t_c} and its standard deviation σ_{t_c} of the largest such cluster, as well as the associated scenario probability defined as the cardinal of the respective cluster divided by the total number of fits. If the largest detected clusters are of similar size, we pick the one with the lower standard deviation of tc.

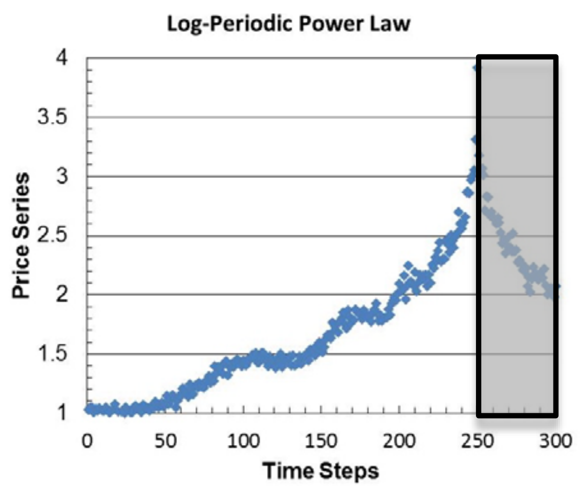
[1] J.-C Gerlach, G. Demos and D. Sornette, Dissection of Bitcoin's Multiscale Bubble History (April 12, 2018). Swiss Finance Institute Research Paper No. 18-30. Available at SSRN: https://ssrn.com/abstract=3164246 or http://dx.doi.org/10.2139/ssrn.3164246

[2] Qun Zhang, Qunzhi Zhang and Didier Sornette, Early warning signals of financial crises with multi-scale quantile regressions of Log-Periodic Power Law Singularities, PLoS ONE 11(11): e0165819. doi:10.1371/journal.pone.0165819, pp. 1-43 (2016)

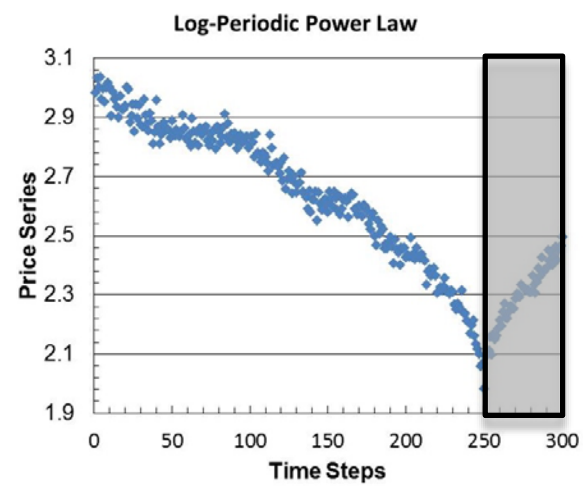
Methodology

We use the Log-Periodic Power Law Singularity (LPPLS) model to hunt for the distinct fingerprint of Bubbles:

1. Price rises faster than exponentially, therefore the logarithm of the price rises faster than linearly;
2. There are accelerating oscillations, with a distinct characteristic.



Positive bubble: imitation in **buying**



Negative bubble: imitation in **selling**

General Results – The Big Picture

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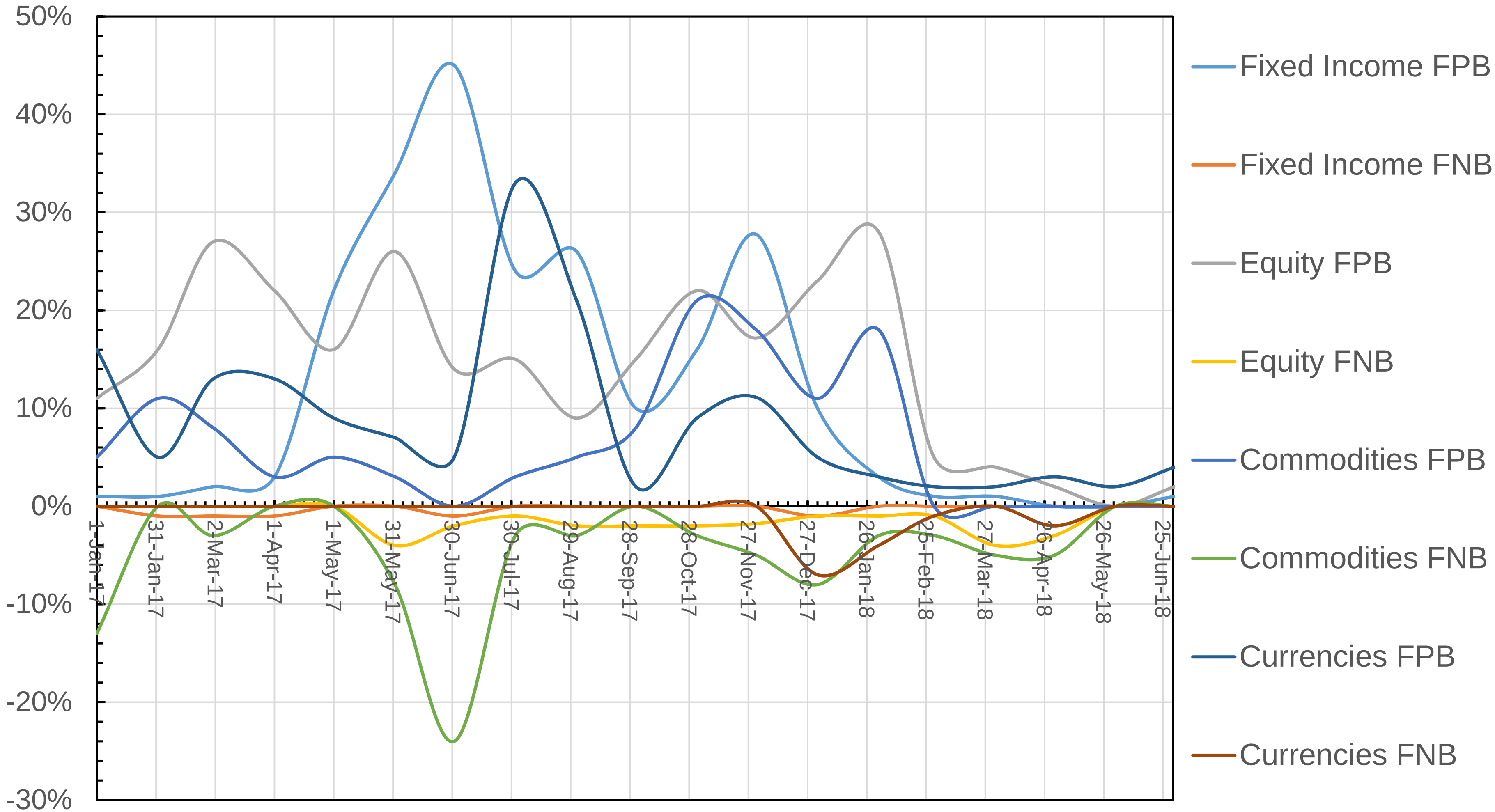
Historical evolution of the fraction of assets within an asset class that show significant bubble signals



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	1	0
	Government Bonds	55	2	0
	Finance and Insurance	21	0	0
	Corporate Bonds	79	0	0
Equity		293	2	0
	Country Indices	72	1	0
	Europe	32	0	0
	United States	189	3	0
Commodities		31	0	0
Forex		101	4	0

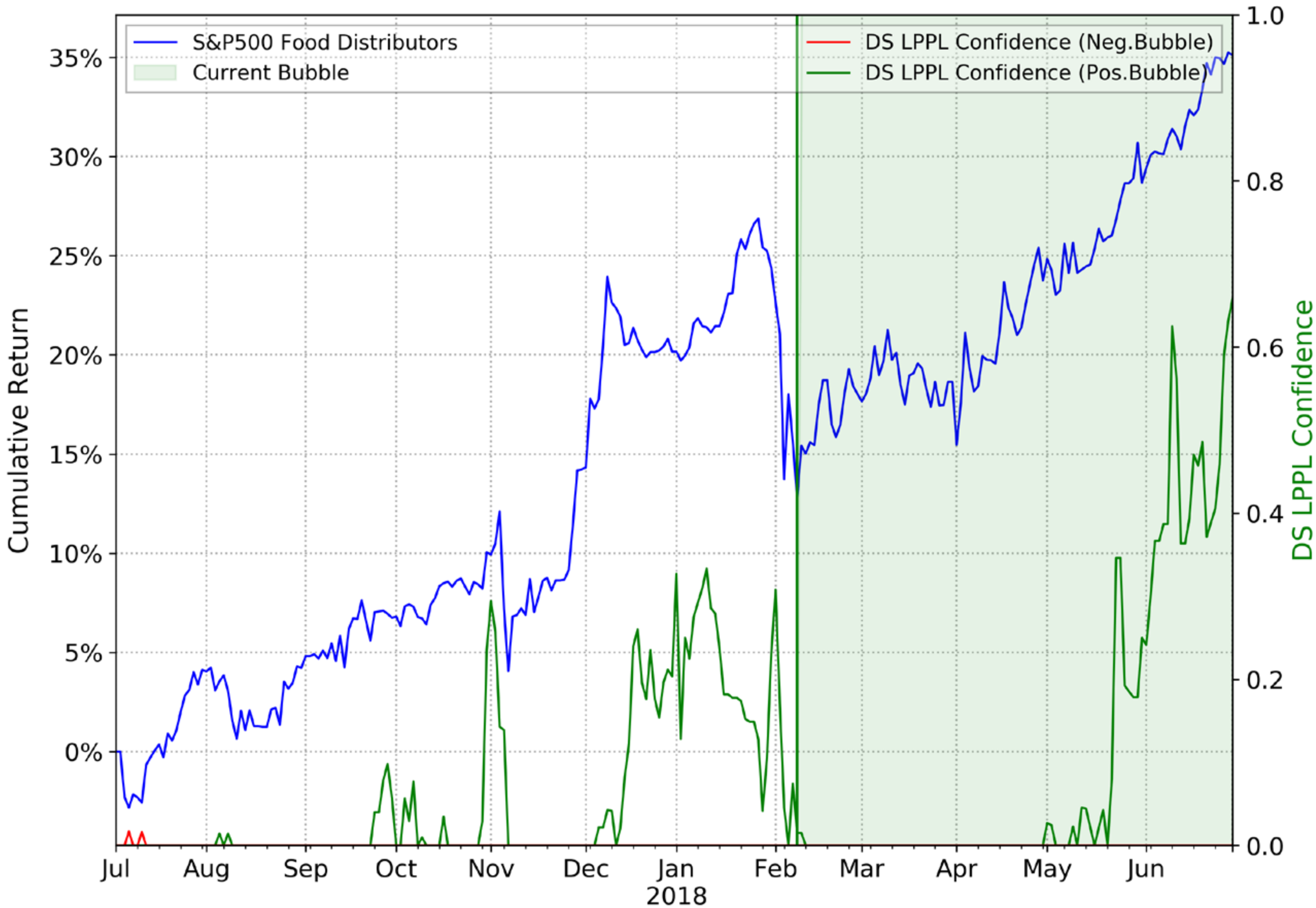
At the beginning of July 2018, the only bond index showing some signs of positive bubble activity is the GEMX Kenya Index of the iBoxx series. The Markit iBoxx GEMX Index family represents the market for accessible local currency emerging market sovereign debt. However, the exponent m is close to 1 and there is barely any super-exponential acceleration and thus even this bubble may be a false positive. Amongst the corporate, as well as financial and insurance bond sectors, no bubble signals are detected this month.

No signs of positive or negative bubble activity are found in the country equity indices asset class. This is also the case for European Equity indices.

Equities - United States

	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	S&P500 Food Distributors	18	149	74	37	2018-07-31	3	47
2	S&P500 Department Stores	22	150	28	25	2018-07-20	1	19
3	S&P500 Movies & Entertainment	19	247	21	20	2018-07-10	6	68
4	S&P500 Data Pro&Out Svs	24	268	11	16	2018-12-29	1	17
5	S&P500 Consumer Durables & App	10	227	15	12	2018-07-09	12	73
Negative Bubbles								
1								

In the United States equity sectors, we detect a small number of indices (3%) that show positive bubble dynamics. At the top of the list, we see the S&P 500 Food Distributors index with a geometric average of bubble size (18%) and confidence indicator (74%) of 37%.
For this index, the probability of the most likely bubble burst scenario is 47%. The critical time is predicted to occur at the end of July, with a low standard deviation of only 3 days. Interestingly, the identified crash scenarios for three of the other assets also predict the critical time to be in July. The remaining scenario predicts the burst time around December 18, 2018.


S&P500 Food Distributors
Current Bubble
DS LPPL Confidence (Neg.Bubble)
DS LPPL Confidence (Pos.Bubble)
Cumulative Return
DS LPPL Confidence
35%
30%
25%
20%
15%
10%
5%
0%
1.0
0.8
0.6
0.4
0.2
0.0
Jul
Aug
Sep
Oct
Nov
Dec
Jan
2018
Feb
Mar
Apr
May
Jun


S&P500 Department Stores
Current Bubble
DS LPPL Confidence (Neg.Bubble)
DS LPPL Confidence (Pos.Bubble)
Cumulative Return
DS LPPL Confidence
60%
50%
40%
30%
20%
10%
0%
-10%
1.0
0.8
0.6
0.4
0.2
0.0
Jul
Aug
Sep
Oct
Nov
Dec
Jan
2018
Feb
Mar
Apr
May
Jun

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								
	-	-	-	-	-	-	-	-
Negative Bubbles								
	-	-	-	-	-	-	-	-

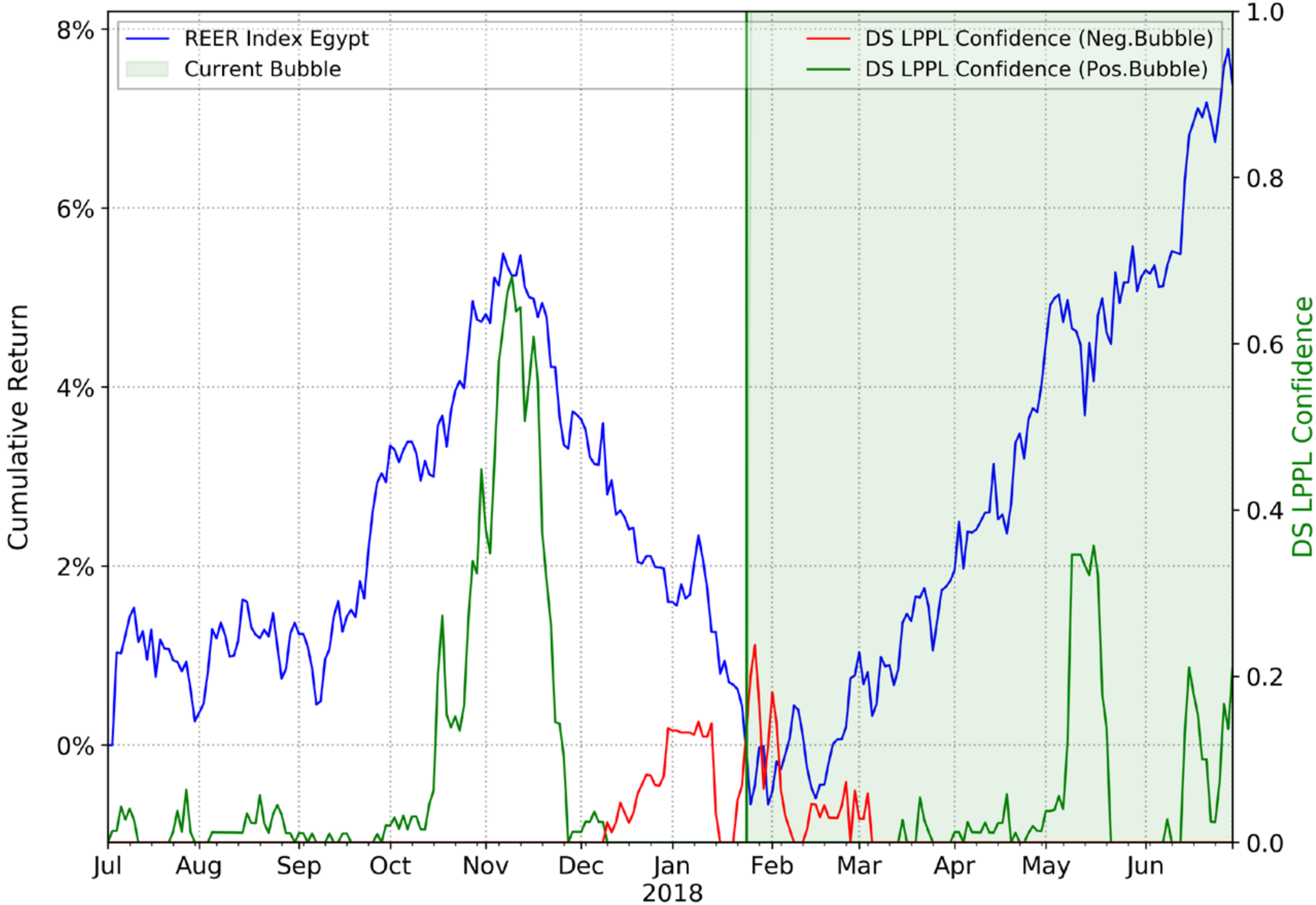
Neither positive nor negative bubble dynamics are identified in any of the analyzed commodities assets.

Currencies – Real Effective Exchange Rates & PCA

	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								
	REER Index Egypt	10	205	84	30	2018-07-03	2	73
	REER Index Ukraine	11	144	11	11	2018-07-04	3	91
Negative Bubbles								

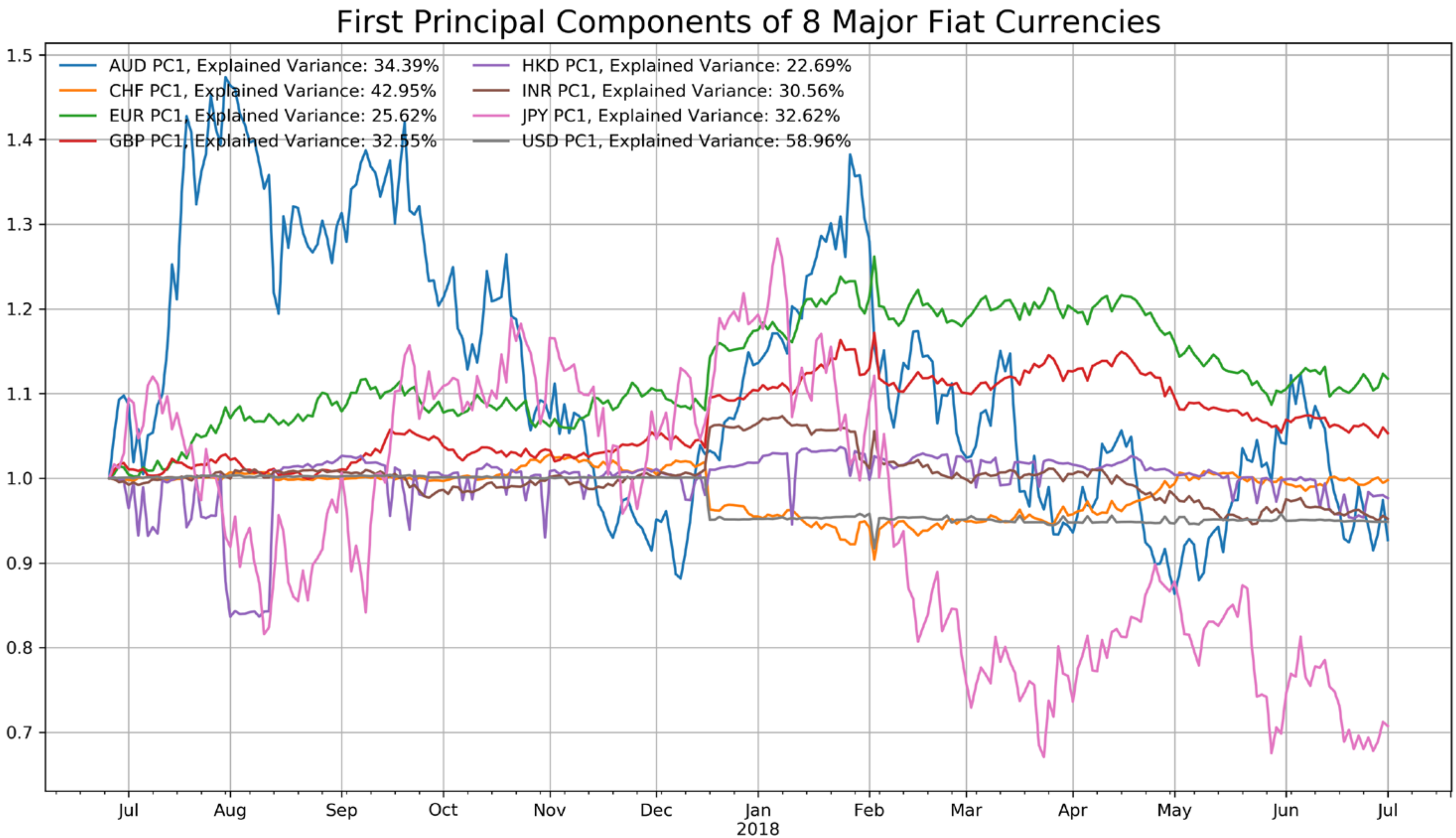
Among currency exchange rates quantified by the REER indices, two currencies out of 25 analysed show positive bubble signals this month. The 'top scorer', the REER Index[1] Egypt is analyzed on the next slide. The depicted plot shows two clear changes of regime in the Egyptian Currency Index that happened within the past year. The first one is the reversion of the positive bubble trend in December 2017. The second more recent reversion of the negative trend to a new phase of positive growth occurred in February 2018. Around the time of both events, corresponding peaks in the positive and negative bubble confidence indicators can be observed. The currently high value of the confidence indicator (84%) could therefore once more be a serious indication for an imminent change in the dynamics of the index.
The Principal Component Analysis was without results of bubble activity this month. The corresponding plot is depicted two slides below.

[1] Real Effective Exchange Rate (REER) is a measure of the trade-weighted average exchange rate of a currency against a basket of currencies after adjusting for inflation differentials with regard to the countries concerned and expressed as an index number relative to a base year. The larger the REER, the stronger the currency.



REER Index Egypt
Current Bubble
DS LPPL Confidence (Neg.Bubble)
DS LPPL Confidence (Pos.Bubble)
Cumulative Return
DS LPPL Confidence
8%
6%
4%
2%
0%
1.0
0.8
0.6
0.4
0.2
0.0
Jul
Aug
Sep
Oct
Nov
Dec
Jan
2018
Feb
Mar
Apr
May
Jun

Currencies – PCA



Currencies – Cryptocurrencies

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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								
	-	-	-	-	-	-	-	-
Negative Bubbles								
	-	-	-	-	-	-	-	-

No super-exponential price patterns are detected amongst the market capitalization time series of the top 1000 cryptocurrencies that are listed on coinmarketcap as of July 1st.

Single Stocks

For 814 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.

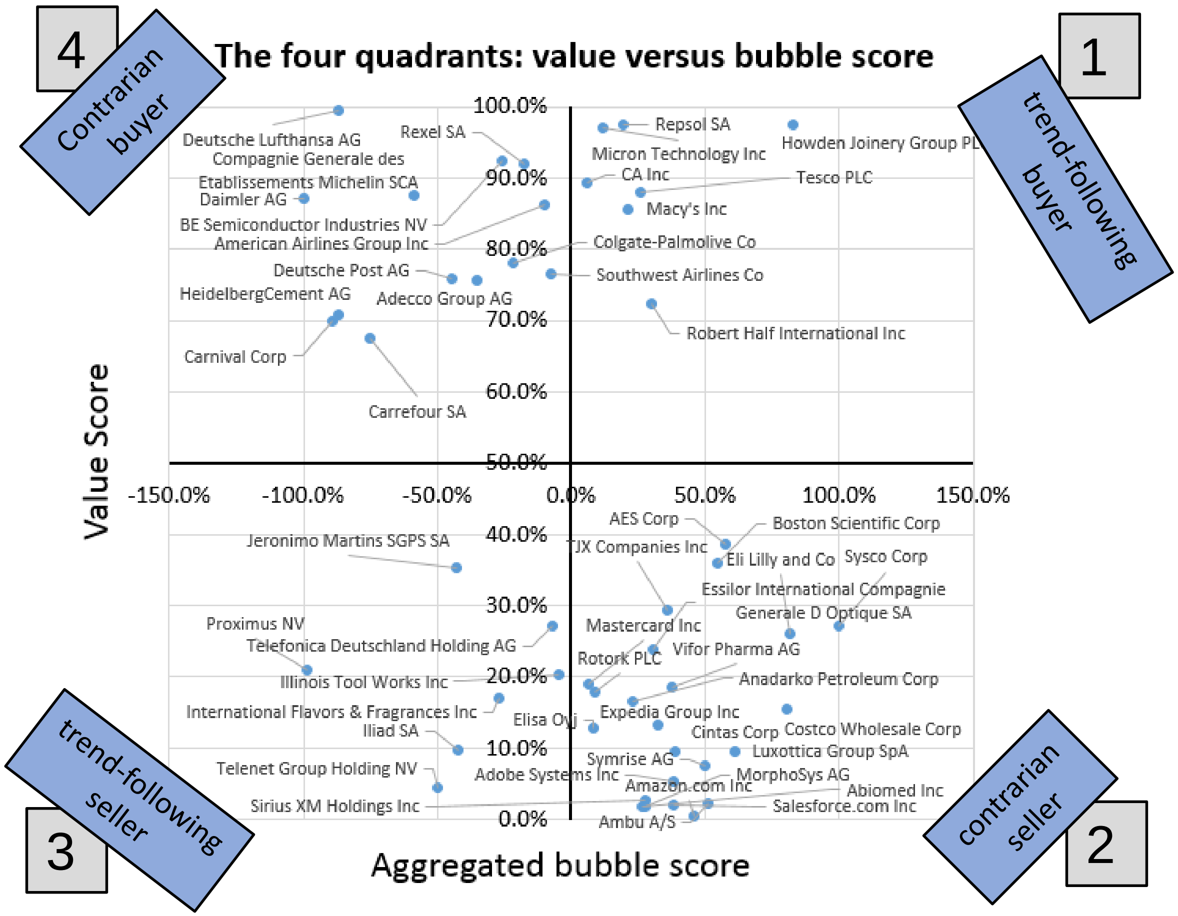
The stocks are the constituents of the Stoxx Europe 600, the S&P 500 and the Nasdaq 100 indices. From these, all doubles and stocks with incomplete data are removed. Because our financial strength indicators are specifically designed for corporates, all financial institutions are taken out of the set 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. Macy's Inc);
2. Quadrant 2: Stocks with a strong positive bubble score and a weak value score (e.g. Amazon.com Inc);
3. Quadrant 3: Stocks with a strong negative bubble score and a weak value score (e.g. Proximus NV);
4. Quadrant 4: Stocks with strong negative bubble score and a strong financial strength (e.g. Carrefour 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.

Single Stocks

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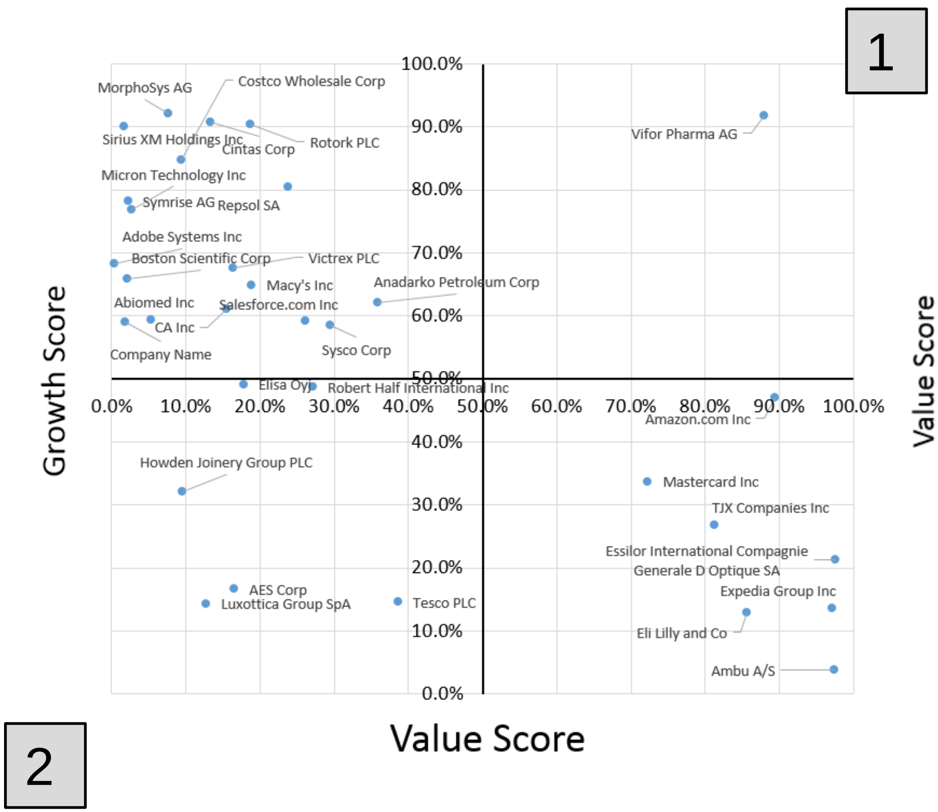
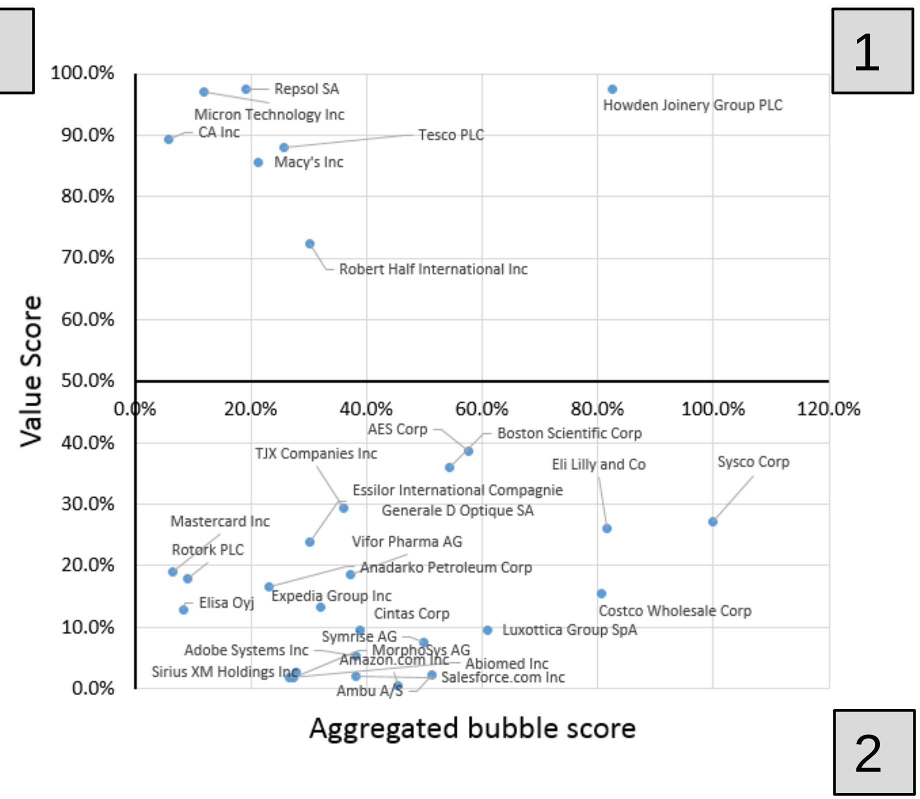
Quadrant 1 and 2 stocks

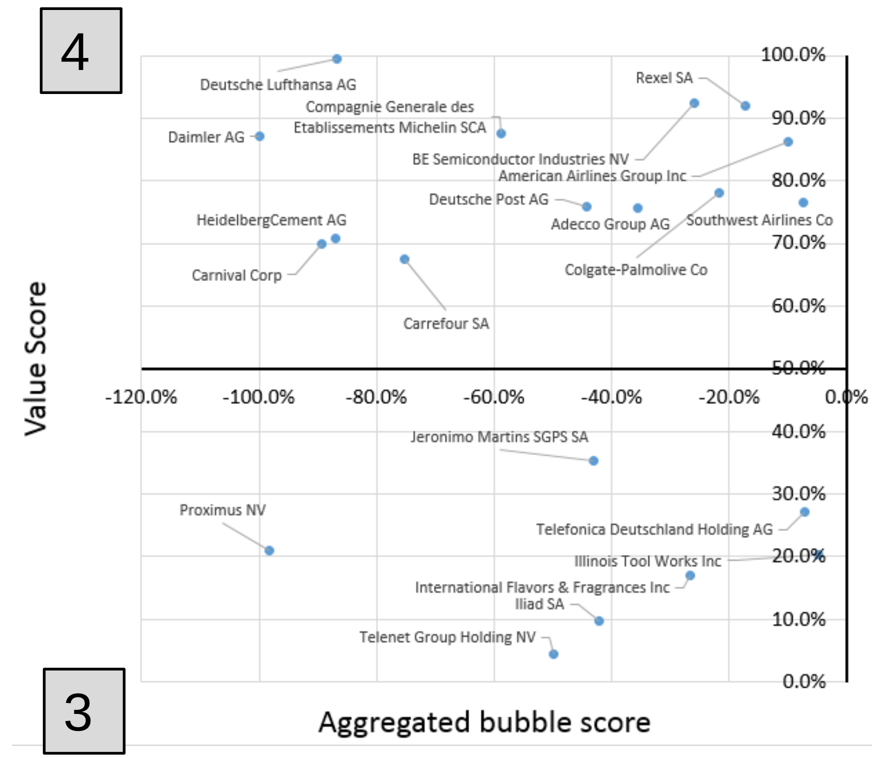
Strong positive bubble signals with strong (respectively weak) fundamentals





Quadrant 3 and 4 stocks

Strong negative bubble signals with weak (respectively strong) fundamentals



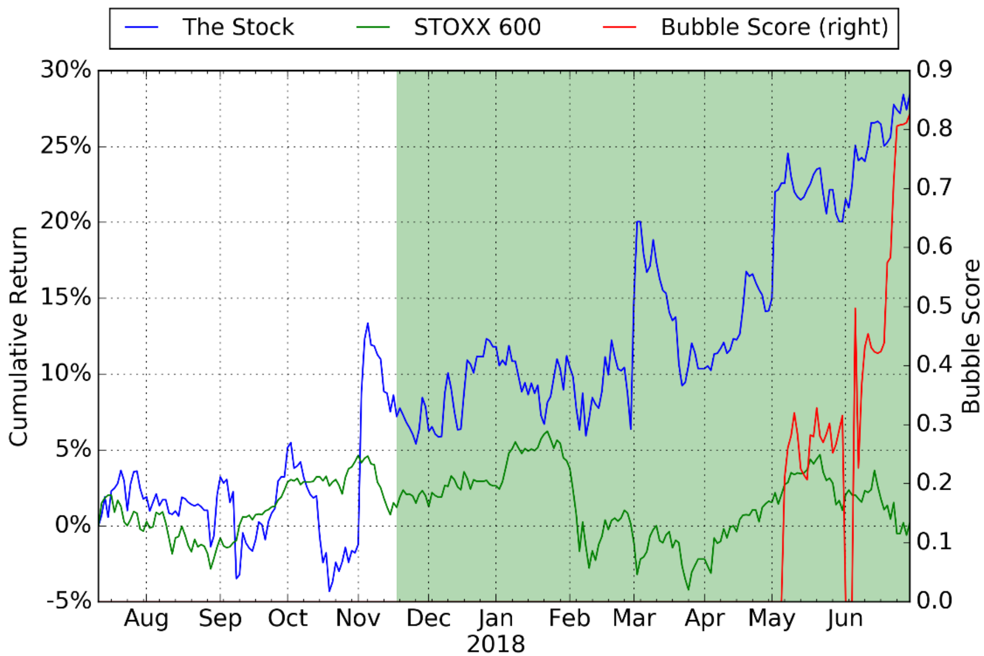
Single Stocks

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
CA Inc	United States of America	Software & Services	3.5%	11.9%	Aug-17	5.8%	89.3%	47.1%
Micron Technology Inc	United States of America	Semiconductors & Semiconductor Equipment	68.5%	68.5%	Jul-17	11.9%	97.1%	13.6%
Repsol SA	Spain	Energy	28.0%	17.9%	Nov-17	19.2%	97.4%	3.8%
Howden Joinery Group PLC	United Kingdom	Capital Goods	26.0%	19.8%	Nov-17	82.6%	97.5%	21.3%
Tesco PLC	United Kingdom	Food & Staples Retailing	48.6%	47.3%	Jul-17	25.7%	88.0%	91.8%
Macy's Inc	United States of America	Retailing	69.4%	56.1%	Nov-17	21.4%	85.7%	12.9%
Robert Half International Inc	United States of America	Commercial & Professional Services	33.0%	22.2%	Dec-17	30.1%	72.3%	33.7%
Victrex PLC	United Kingdom	Materials	55.2%	18.0%	Feb-18	74.5%	81.3%	26.8%
Telefonaktiebolaget LM Ericsson	Sweden	Technology Hardware & Equipment	11.5%	31.3%	Nov-17	34.7%	76.2%	2.7%
Swedish Match AB	Sweden	Food, Beverage & Tobacco	50.6%	58.1%	Sep-17	41.8%	97.2%	65.4%

Single Stocks - Quadrant 1 stocks

Quadrant 1 stocks: strong positive bubble signals with strong fundamentals
Example: Howden Joinery Group PLC.

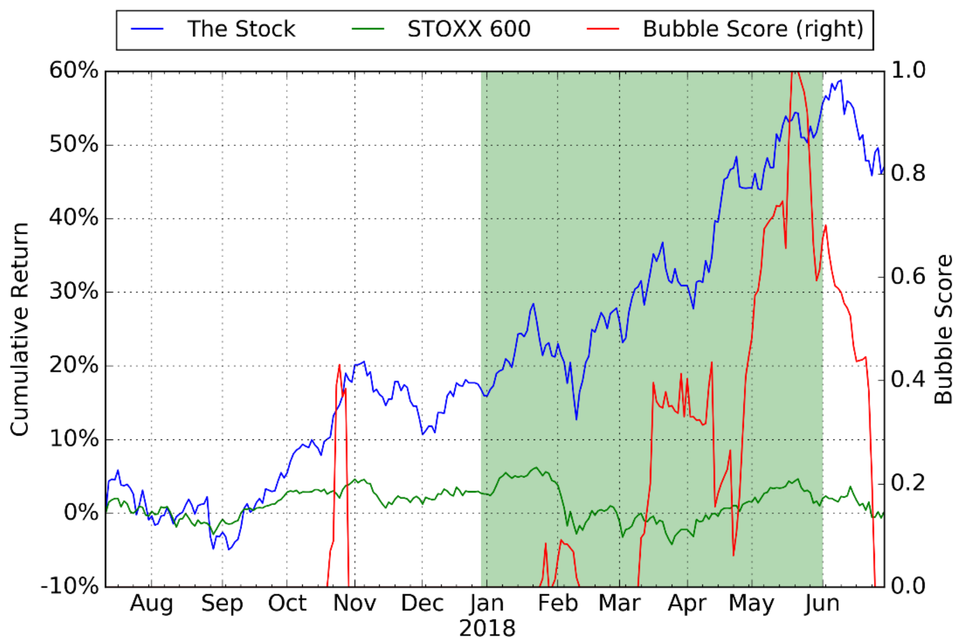


The above graph shows the one year cumulative return of the stock in blue (left hand scale), STOXX 600 in green (left hand scale) and the calculated DS LPPLS Bubble Score in red (right hand scale). The green shaded period is the strong positive bubble we identified. The Bubble Score of this seven month bubble has reached 82.6% with a bubble size 19.8%.

Single Stocks - Quadrant 1 stocks

Last month example: strong positive bubble signals with strong fundamentals, Stora Enso Oyj.

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. Note that the stock had a strong correction in the past month, which is in agreement with the DS LPPLS indicator, 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
Abiomed Inc	United States of America	Health Care Equipment & Services	186.1%	174.7%	Aug-17	26.7%	1.8%	59.1%
Adobe Systems Inc	United States of America	Software & Services	68.1%	41.6%	Oct-17	38.2%	5.3%	59.4%
Amazon.com Inc	United States of America	Retailing	69.9%	51.7%	Nov-17	45.5%	0.4%	68.3%
Costco Wholesale Corp	United States of America	Food & Staples Retailing	36.1%	14.3%	Feb-18	80.7%	15.6%	61.0%
Cintas Corp	United States of America	Commercial & Professional Services	46.3%	25.7%	Oct-17	39.0%	9.4%	84.7%
Expedia Group Inc	United States of America	Retailing	-21.4%	15.6%	Feb-18	32.1%	13.4%	90.7%
Sirius XM Holdings Inc	United States of America	Media	24.7%	19.2%	Aug-17	27.8%	2.7%	77.0%
MorphoSys AG	Germany	Pharmaceuticals, Biotechnology & Life Sciences	68.2%	42.4%	Feb-18	27.3%	1.7%	90.1%
Symrise AG	Germany	Materials	22.8%	14.7%	Feb-18	50.0%	7.6%	92.2%
Ambu A/S	Denmark	Health Care Equipment & Services	161.0%	76.2%	Feb-18	51.3%	2.2%	78.2%
Essilor International Compagnie Generale D Optique SA	France	Health Care Equipment & Services	6.2%	13.6%	Feb-18	30.2%	23.8%	80.4%
Luxottica Group SpA	Italy	Consumer Durables & Apparel	6.7%	11.9%	Feb-18	60.9%	9.6%	32.1%
Elisa Oyj	Finland	Telecommunication Services	14.9%	14.7%	Oct-17	8.4%	12.7%	14.3%
Rotork PLC	United Kingdom	Capital Goods	38.0%	30.0%	Sep-17	9.0%	17.8%	49.1%
Vifor Pharma AG	Switzerland	Pharmaceuticals, Biotechnology & Life Sciences	49.1%	49.8%	Sep-17	37.3%	18.6%	90.4%
AES Corp	United States of America	Utilities	21.7%	27.8%	Nov-17	57.6%	38.6%	14.6%
Anadarko Petroleum Corp	United States of America	Energy	64.8%	51.1%	Sep-17	23.1%	16.5%	16.7%
Boston Scientific Corp	United States of America	Health Care Equipment & Services	18.5%	23.9%	Feb-18	54.3%	35.9%	62.1%
Salesforce.com Inc	United States of America	Software & Services	52.3%	42.8%	Aug-17	38.1%	2.1%	65.9%
Eli Lilly and Co	United States of America	Pharmaceuticals, Biotechnology & Life Sciences	1.6%	11.2%	Feb-18	81.6%	26.1%	59.2%
Mastercard Inc	United States of America	Software & Services	56.6%	34.4%	Oct-17	6.6%	18.9%	65.0%
Sysco Corp	United States of America	Food & Staples Retailing	35.5%	16.9%	Feb-18	100.0%	27.1%	48.8%
TJX Companies Inc	United States of America	Retailing	36.0%	36.8%	Jul-17	36.0%	29.4%	58.6%
Assa Abloy AB	Sweden	Capital Goods	4.5%	8.6%	Oct-17	6.9%	16.3%	67.6%

Single Stocks - Quadrant 2 stocks

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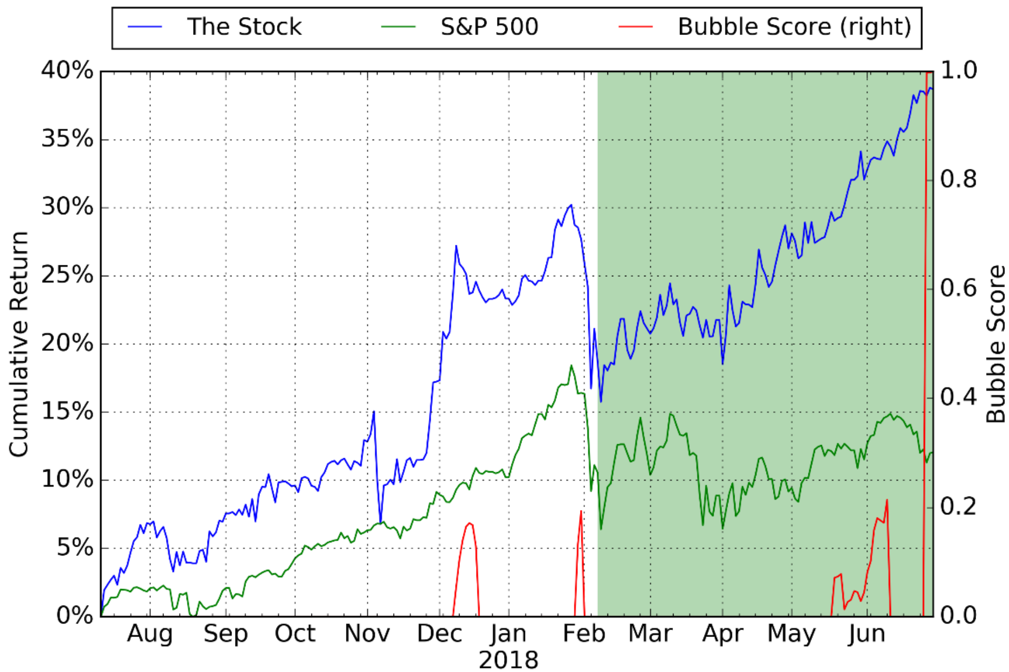
Quadrant 2 stocks: strong positive bubble signals with weak fundamentals

Example: Sysco Corp.

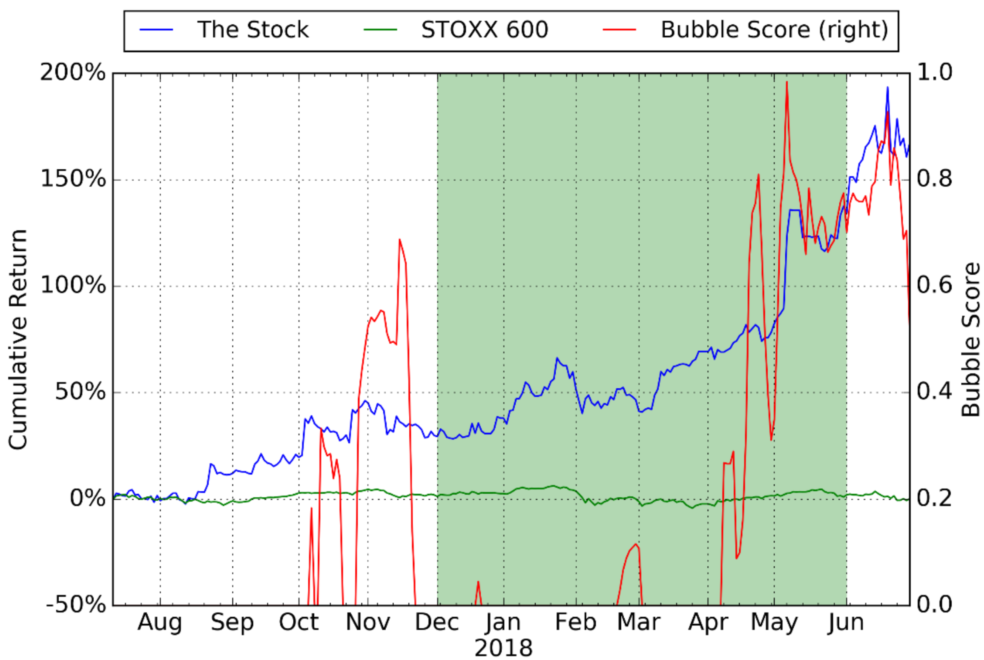


The above graph shows the one year cumulative return of the stock in blue (left hand scale), S&P 500 in green (left hand scale) and the calculated DS LPPLS Bubble Score in red (right hand scale). The green shaded period is the strong positive bubble we identified. The Bubble Score of this five month bubble has reached 100% with a bubble size 16.9%. 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, Ambu 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 in last month. Note that the stock price seems to have started a change of regime, with higher volatility. According to our classification, increased volatility and a possible significant correction could be expected.



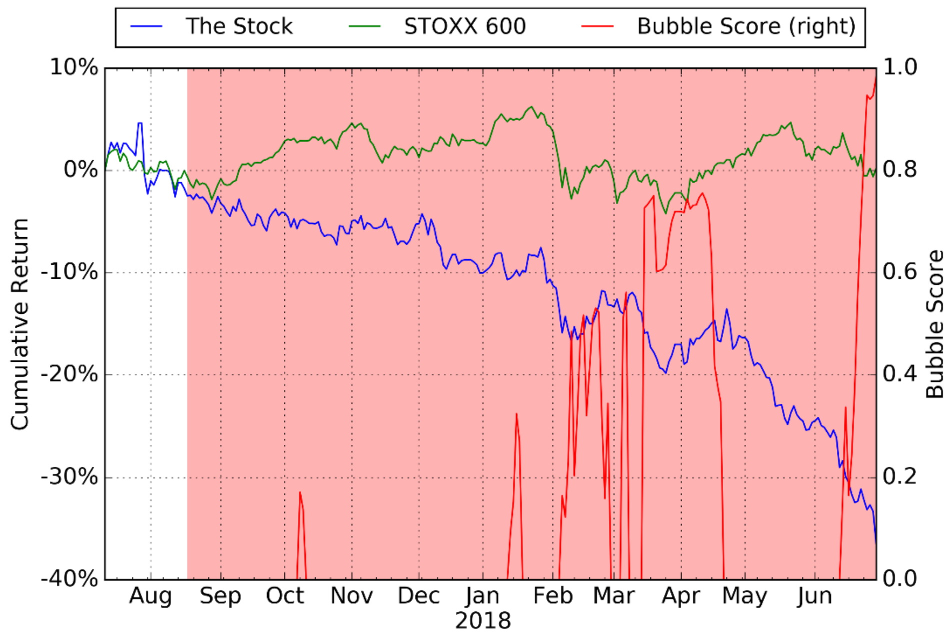
Single Stocks - Quadrant 3 stocks

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
Proximus NV	Belgium	Telecommunication Services	-38.2%	-34.9%	Aug-17	-98.3%	21.0%	93.4%
Telenet Group Holding NV	Belgium	Media	-28.4%	-32.9%	Nov-17	-49.9%	4.5%	89.7%
Telefonica Deutschland Holding AG	Germany	Telecommunication Services	-25.2%	-25.2%	Jul-17	-7.3%	27.2%	97.9%
Iliad SA	France	Telecommunication Services	-35.9%	-31.7%	Feb-18	-42.2%	9.8%	96.0%
Jeronimo Martins SGPS SA	Portugal	Food & Staples Retailing	-29.9%	-27.1%	Aug-17	-43.0%	35.3%	90.3%
International Flavors & Fragrances Inc	United States of America	Materials	-6.6%	-16.4%	Oct-17	-26.7%	17.0%	55.1%
Illinois Tool Works Inc	United States of America	Capital Goods	-4.3%	-13.9%	Nov-17	-4.9%	20.2%	76.6%
Electrolux AB	Sweden	Consumer Durables & Apparel	-27.3%	-29.4%	Nov-17	-21.2%	39.0%	1.7%

Single Stocks - Quadrant 3 stocks

Quadrant 3 stocks: strong negative bubble signals with weak fundamentals
Example: Proximus NV.

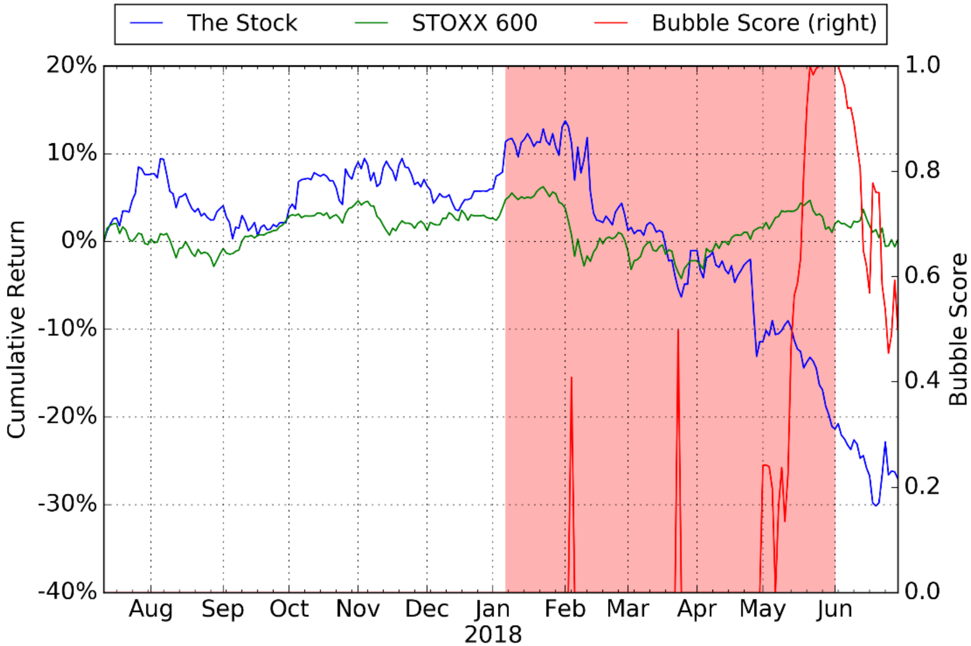


The above graph shows the one year cumulative return of the stock in blue (left hand scale), STOXX 600 in green (left hand scale) and the calculated DS LPPLS Bubble Score in red (right hand scale). The red shaded period is the strong negative bubble we identified. The Bubble Score of this ten and a half month bubble has reached 98.3% with a bubble size -34.9%.

Single Stocks - Quadrant 3 stocks

Last month example: strong negative bubble signals with weak fundamentals, Telenet Group Holding NV.

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. Note that, after continuing to drop, the stock has had a small rebound and higher volatility, which is in agreement with our 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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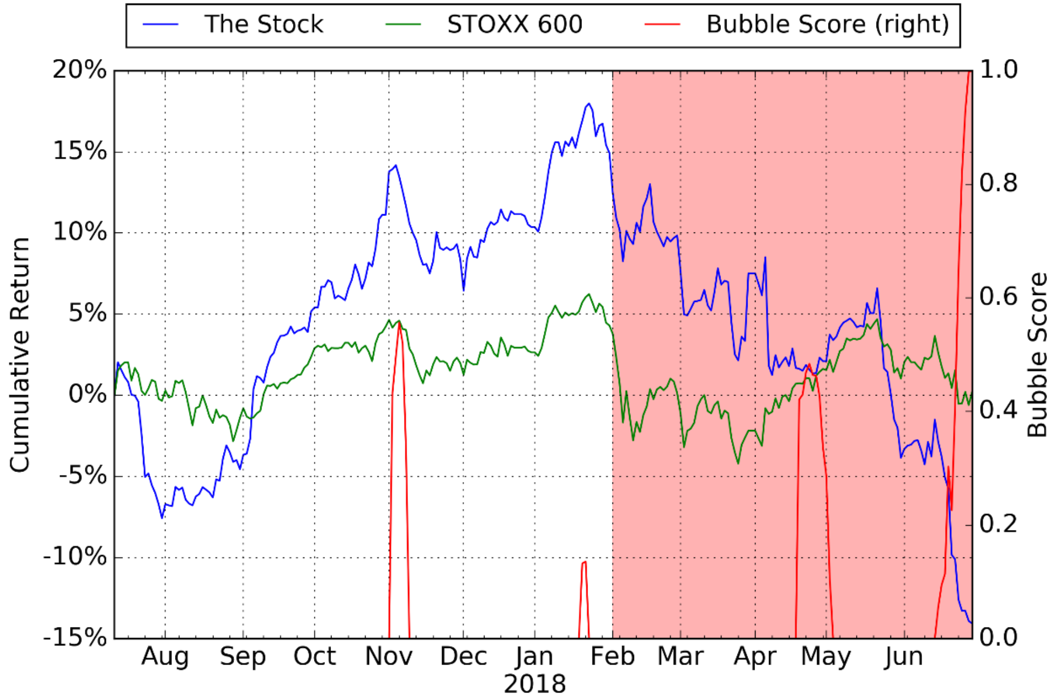
Quadrant 4 stocks: strong negative bubble signals with strong fundamentals

Company Name	Country of Headquarters	GICS Industry Group Name	Yearly Return	Bubble Size	Bubble Start	Bubble Score	Value Score	Growth Score
American Airlines Group Inc	United States of America	Transportation	-29.5%	-21.9%	Oct-17	-10.0%	86.3%	39.3%
Daimler AG	Germany	Automobiles & Components	-15.4%	-23.6%	Feb-18	-100.0%	87.0%	28.7%
Deutsche Post AG	Germany	Transportation	-18.2%	-25.8%	Sep-17	-44.3%	75.9%	91.4%
HeidelbergCement AG	Germany	Materials	-16.9%	-16.2%	Feb-18	-87.0%	70.8%	98.9%
Deutsche Lufthansa AG	Germany	Transportation	-1.7%	-22.1%	Feb-18	-86.7%	99.5%	0.6%
Carrefour SA	France	Food & Staples Retailing	-35.9%	-27.2%	Jan-18	-75.3%	67.5%	96.7%
Compagnie Generale des Etablissements Michelin SCA	France	Automobiles & Components	-14.7%	-16.9%	Feb-18	-58.9%	87.6%	10.2%
Rexel SA	France	Capital Goods	-12.5%	-19.3%	Oct-17	-17.3%	92.0%	98.8%
BE Semiconductor Industries NV	Netherlands	Semiconductors & Semiconductor Equipment	-4.9%	-31.3%	Oct-17	-25.9%	92.4%	63.4%
Adecco Group AG	Switzerland	Commercial & Professional Services	-18.2%	-23.3%	Oct-17	-35.5%	75.7%	83.2%
Carnival Corp	United States of America	Consumer Services	-13.4%	-18.1%	Feb-18	-89.4%	70.0%	20.2%
Colgate-Palmolive Co	United States of America	Household & Personal Products	-10.3%	-11.5%	Nov-17	-21.8%	78.1%	68.6%
Southwest Airlines Co	United States of America	Transportation	-18.0%	-16.1%	Nov-17	-7.4%	76.6%	56.9%
Getinge AB	Sweden	Health Care Equipment & Services	-39.5%	-31.7%	Dec-17	-20.8%	80.9%	0.5%

Single Stocks - Quadrant 4 stocks

Quadrant 4 stocks: strong negative bubble signals with strong fundamentals
Example: Daimler AG.

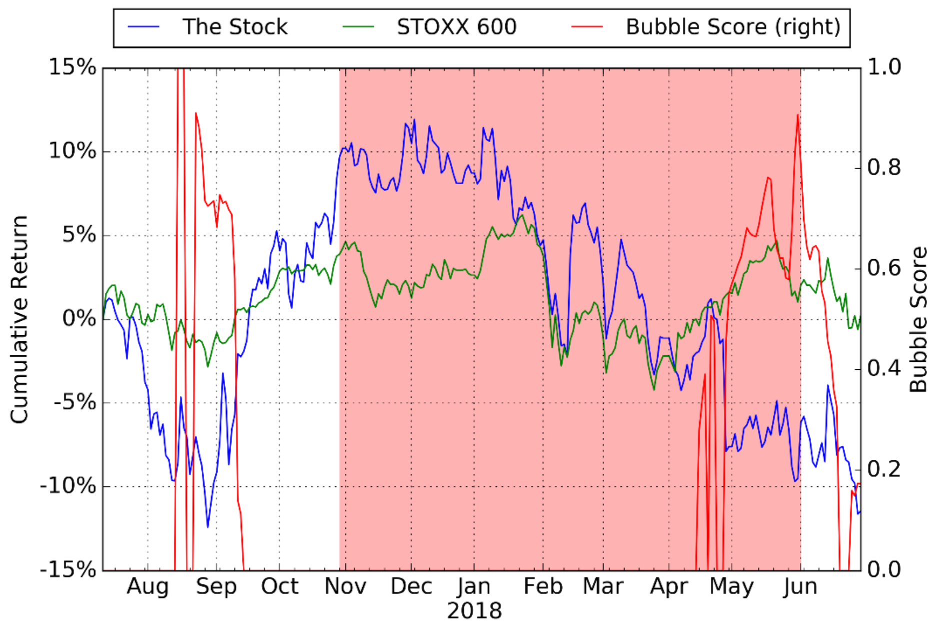


The above graph shows the one year cumulative return of the stock in blue (left hand scale), STOXX 600 in green (left hand scale) and the calculated DS LPPLS Bubble Score in red (right hand scale). The red shaded period is the strong negative bubble we identified. The Bubble Score of this five month bubble has reached 100% with a bubble size -23.6%. 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, Rexel SA.

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 first rebounded but then continued to drop with higher volatility over the second half of June 2018, which is in contradiction with our DS LPPLS indicator and strong fundamentals. We still identify it with strong negative bubble signals this month. We expect this stock to rebound in the future due to the strong fundamentals and following its neglect by investors in previous months.



Sectors

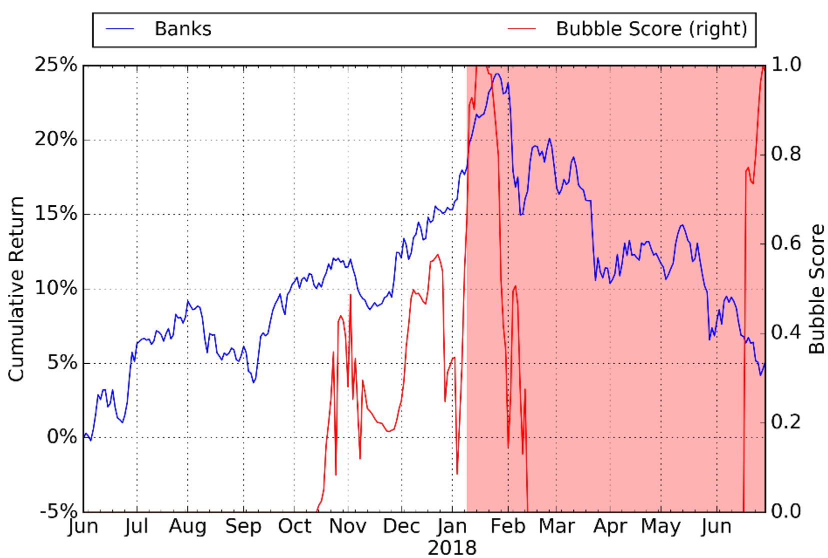
GICS Industry Group Name	Yearly Return		Bubble Size		Bubble Score		Value Score		Growth Score	
	Jul 1st	Jun 1st	Jul 1st	Jun 1st	Jul 1st	Jun 1st	Jul 1st	Jun 1st	Jul 1st	Jun 1st
Pharmaceuticals, Biotechnology & Life Sciences	-1.7%	-0.3%	0.0%	0.0%	0.0%	0.0%	63.6%	64.0%	56.7%	56.9%
Consumer Services	5.4%	9.2%	0.0%	0.0%	0.0%	0.0%	28.0%	27.4%	46.7%	47.7%
Retailing	40.5%	34.8%	0.0%	0.0%	0.0%	0.0%	17.6%	17.9%	57.6%	57.6%
Transportation	6.2%	12.2%	0.0%	0.0%	0.0%	0.0%	57.1%	57.4%	55.5%	55.8%
Consumer Durables & Apparel	15.0%	18.1%	0.0%	0.0%	0.0%	0.0%	36.6%	38.1%	54.9%	54.1%
Semiconductors & Semiconductor Equipment	23.8%	36.0%	0.0%	0.0%	0.0%	0.0%	64.1%	64.8%	29.8%	31.0%
Technology Hardware & Equipment	20.6%	25.6%	0.0%	0.0%	0.0%	0.0%	70.5%	71.6%	39.6%	40.0%
Automobiles & Components	3.9%	12.9%	0.0%	0.0%	0.0%	0.0%	76.6%	77.4%	50.3%	50.9%
Telecommunication Services	-6.0%	-8.7%	-9.0%	0.0%	-16.3%	0.0%	56.9%	55.2%	38.0%	40.9%
Energy	20.0%	19.3%	0.0%	0.0%	0.0%	0.0%	49.7%	50.3%	52.8%	52.5%
Software & Services	24.7%	29.2%	0.0%	0.0%	0.0%	0.0%	35.8%	36.2%	46.9%	47.8%
Materials	8.4%	16.0%	0.0%	0.0%	0.0%	0.0%	51.0%	51.0%	47.3%	46.3%
Health Care Equipment & Services	14.0%	14.7%	0.0%	0.0%	0.0%	0.0%	63.9%	64.9%	58.1%	58.0%
Capital Goods	2.3%	7.5%	0.0%	0.0%	0.0%	0.0%	45.3%	45.7%	53.3%	53.7%
Media	-2.5%	-10.1%	0.0%	0.0%	0.0%	0.0%	40.0%	41.8%	52.6%	52.6%
Commercial & Professional Services	9.9%	7.4%	0.0%	0.0%	0.0%	0.0%	28.5%	28.7%	51.4%	49.4%
Food & Staples Retailing	8.8%	1.2%	0.0%	0.0%	0.0%	0.0%	59.2%	56.7%	60.3%	60.3%
Household & Personal Products	-0.2%	-5.3%	0.0%	0.0%	0.0%	0.0%	35.3%	35.2%	50.1%	49.8%
Food, Beverage & Tobacco	-7.4%	-11.3%	0.0%	-11.1%	0.0%	-27.3%	42.7%	42.5%	58.3%	58.7%
Utilities	0.6%	-5.4%	0.0%	0.0%	0.0%	0.0%	52.3%	52.5%	43.3%	43.2%
Insurance	-1.9%	4.2%	0.0%	0.0%	0.0%	0.0%	-	-	-	-
Real Estate	3.5%	-0.3%	0.0%	0.0%	0.0%	0.0%	-	-	-	-
Diversified Financials	6.1%	12.6%	0.0%	0.0%	0.0%	0.0%	-	-	-	-
Banks	-1.9%	5.6%	-11.0%	0.0%	-98.5%	0.0%	-	-	-	-

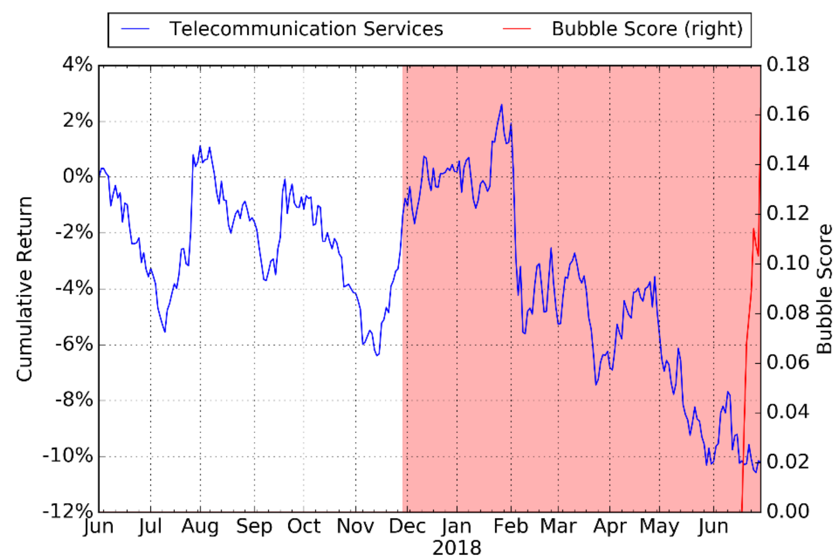
Sectors

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 only 2 industry groups with a negative bubble score: *Banks*, and *Telecommunication Services*, as shown in the figure below. These two industry groups have the worst performances this year among other industry groups.

The bubble score of *Banks* reached 98.5% in recent days, indicating a high probability of a rebound in the future. However, due to the flattening yield curve, there are worries about the earning growth of banks. Regarding *Telecommunication Services*, the current regime may continue for a while due to the moderate bubble.





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

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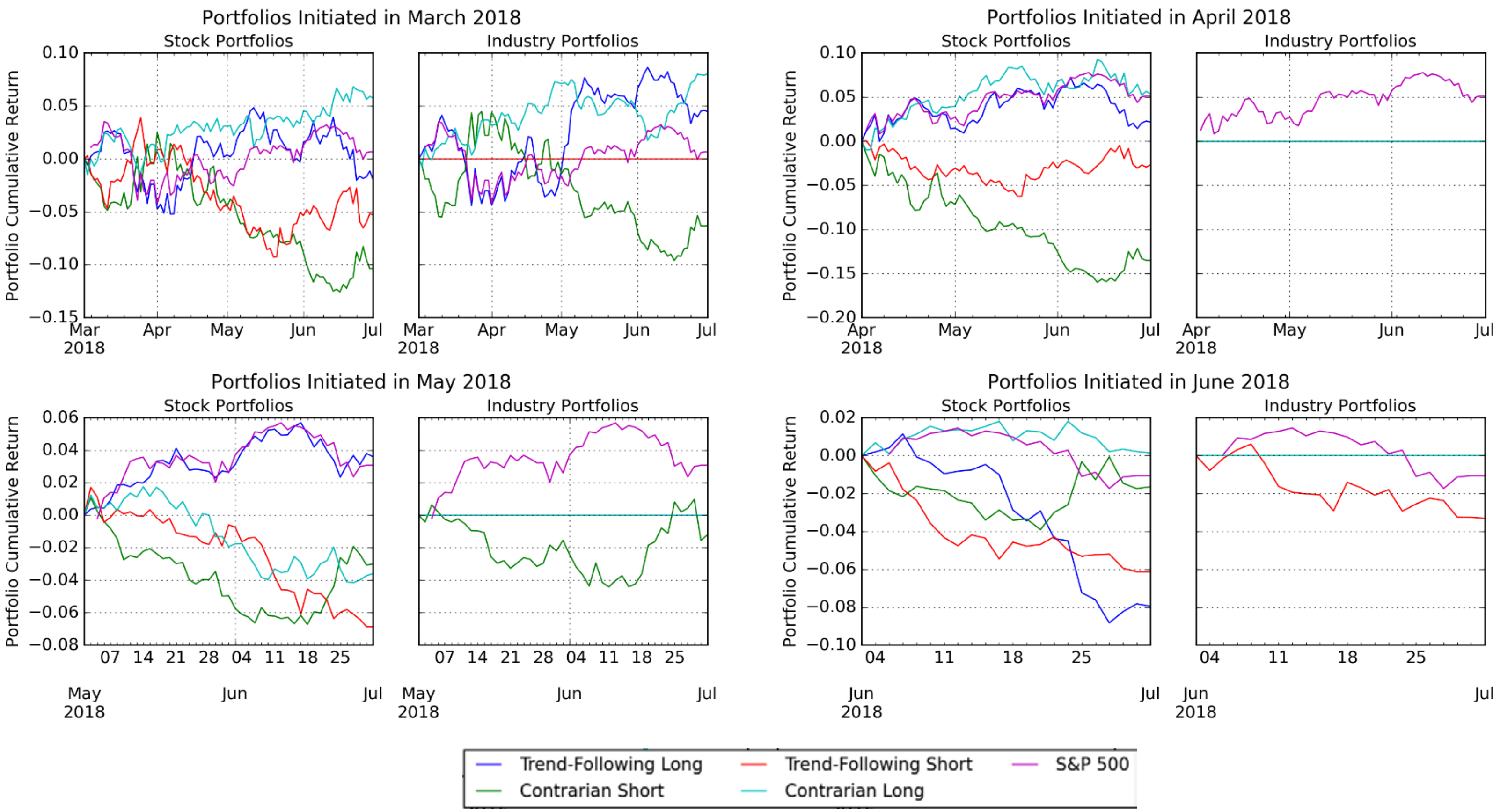


This month, we find that Contrarian Long Portfolios initiated in March and April 2018 are outperforming among others, while they are underperforming in May 2018. Contrarian Portfolios are more delicate to use due to their sensitivity to timing the expected reversal and exhibit very volatile performances, 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.

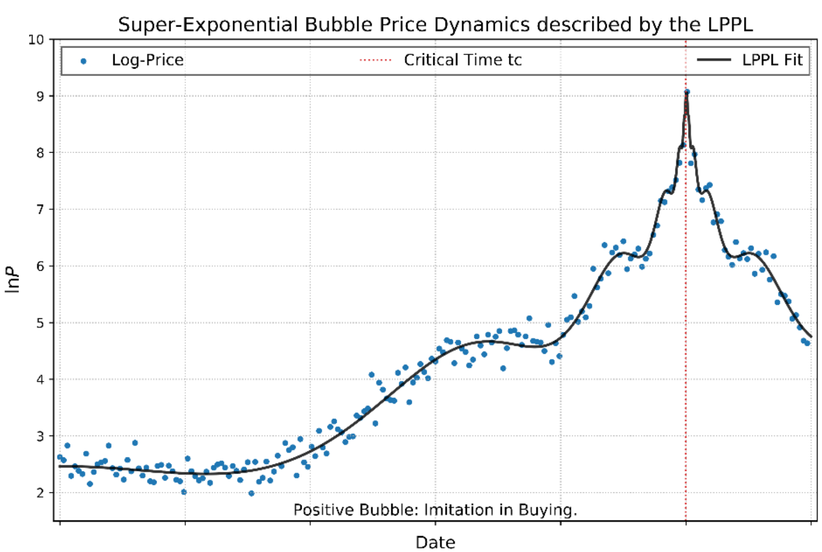
Appendix

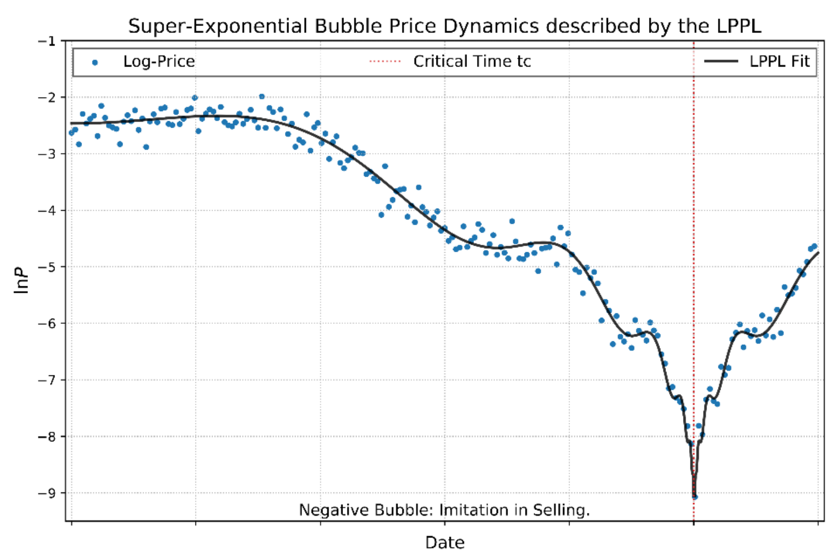
Methodology

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:

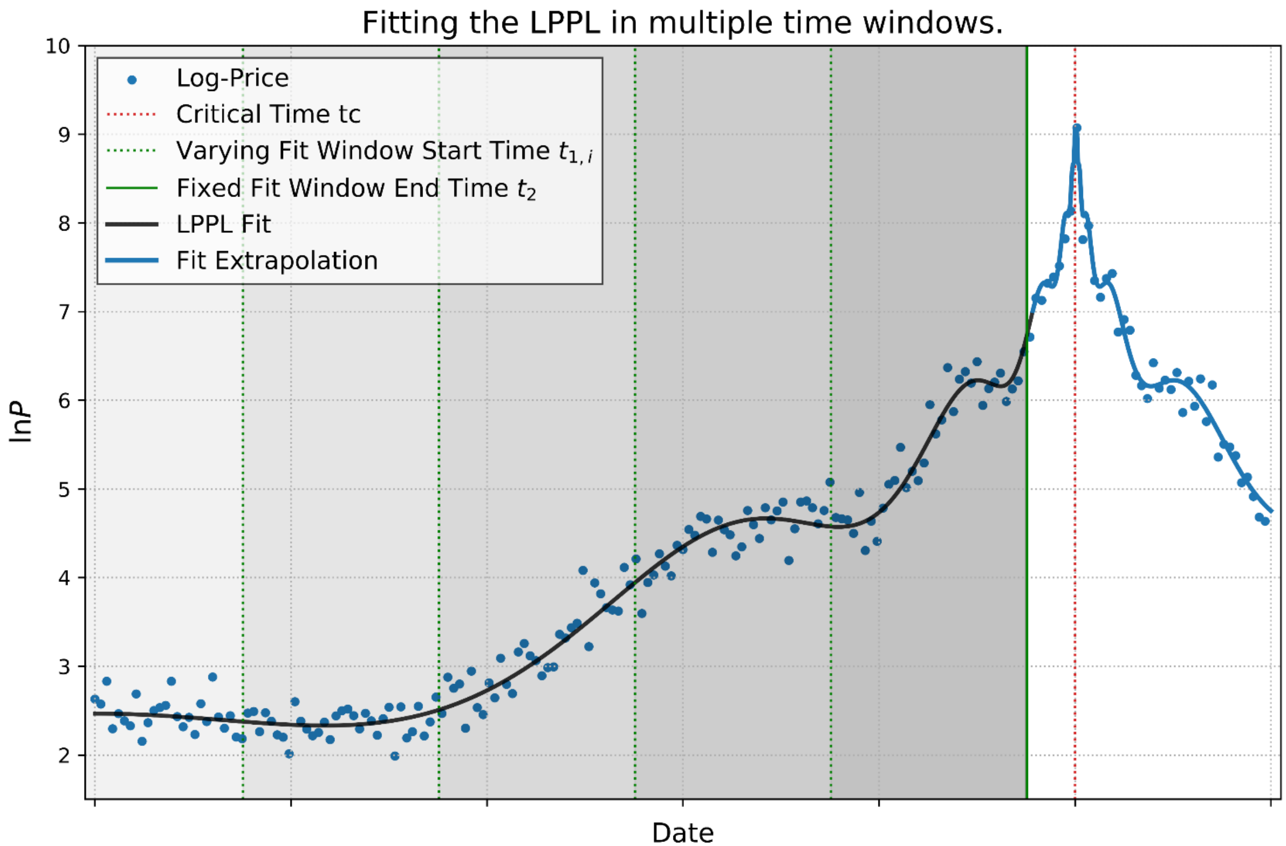
$$LPPLS \coloneqq E[\ln P(t)] = A + B(t_c - t)^m + (t_c - t)^m [C_1 \cos(\omega \ln(t_c - t)) + C_2 \sin(\omega \ln(t_c - t))]$$

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



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

kmeans Clustering for Critical Time Prediction

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Following the methodology established in Gerlach, Demos and Sornette [1], we employ kmeans 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.

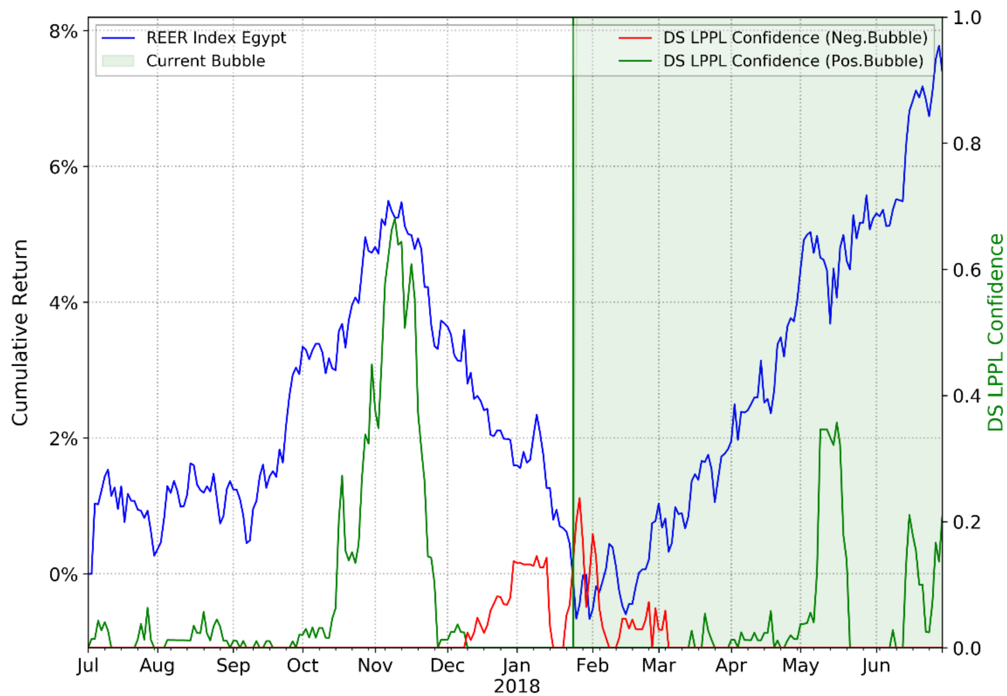
The first section provides asset and estimated bubble characteristics (size and duration), as well as the value of the confidence indicator. We rank assets according to their geometric average of the absolute of bubble size and confidence indicator. In this way, we incorporate the bubble size into the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

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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