Avoiding Bubbles

Contents

Introduction

In this notebook I compare the performance of two portfolios: an equally weighted portfolio and a portfolio whose weights are determined by a bubble indicator. The backtest runs from from June 30, 2016 through June 30, 2021. The portfolios are constructed from the following intstruments.

ETF Ticker	Allocation	Underlying Asset	Description
VTI	20%	Equity	Seeks to track the performance of the CRSP US Total Market Index. Large-, mid-, and small-cap equity diversified across growth and value styles.
VTV	20%	Equity	Seeks to track the performance of the CRSP US Large Cap Value Index, which measures the investment return of large-capitalization value stocks.
VBR	20%	Equity	Seeks to track the performance of the CRSP US Small Cap Value Index, which measures the investment return of small-capitalization value stocks.
TLT	20%	Debt	The iShares 20+ Year Treasury Bond ETF seeks to track the investment results of an index composed of U.S. Treasury bonds with remaining maturities greater than twenty years.
AGG	20%	Debt	The iShares Core U.S. Aggregate Bond ETF seeks to track the investment results of an index composed of the total U.S. investment-grade bond market.

Since the equally weighted portfolio represents 60% equities and 40% debt, a fair benchmark could be 60% VTI (Total Equity Market) and 40% AGG (Total Bond Market). This benchmark is created in the **Organizing Data, Building Benchmark & Portfolio, Determining Cumulative Returns** section.

General Imports and Constants

Below I load the third party libraries for use in the project. Note that the `utils` import includes much of the helper functions used in the notebook.

I also define a few of the constants used throughout the notebook.

In [1]:

```
from datetime import datetime
from matplotlib import pyplot as plt
from multiprocessing import cpu_count
from lppls import lppls
import numpy as np
from os.path import exists
import pandas as pd
import time
import yfinance as yf

from utils import plotting as plt_u # import utility functions for plotting

START = '2016-06-30'
END = '2021-06-30'
LOOKBACK = 21 * 6 # 21 days in a trading month
UNIVERSE_CSV = 'data/universe.csv'
LPPLS_CONF_CSV = 'data/confidence.csv'
CPU_CORES = max(1, cpu_count() // 2)  # only let the LPPLS number cruncher use h
BUBBLE_THRESHOLD = 0.15
```

Fetching Universe Data (Yahoo! Finance)

Yahoo! Finance computes an Adjusted Closing price that factors in all splits and dividends.
https://help.yahoo.com/kb/SLN28256.html

In [2]:

```
tickers = ['TLT', 'VTI', 'VTV', 'VBR', 'AGG']

if not exists(UNIVERSE_CSV):
    print('fetch data from Yahoo! Finance')
    adj_close_list = []
    for ticker in tickers:
        ticker_module = yf.Ticker(ticker)
        data = yf.download(ticker, start='2016-06-30', end='2021-06-30')
        adj_close = data['Adj Close']
        adj_close.rename(f'{ticker} Adj Close', inplace=True)
        adj_close_list.append(adj_close)
    # combine all dataframes into a single dataframe
    df_adj_close = pd.concat(adj_close_list, axis=1)
    df_adj_close.to_csv(UNIVERSE_CSV)
else:
    print('load data from cache')
    df_adj_close = pd.read_csv(UNIVERSE_CSV, index_col='Date', parse_dates=True)
```

```
load data from cache
```

In [3]:

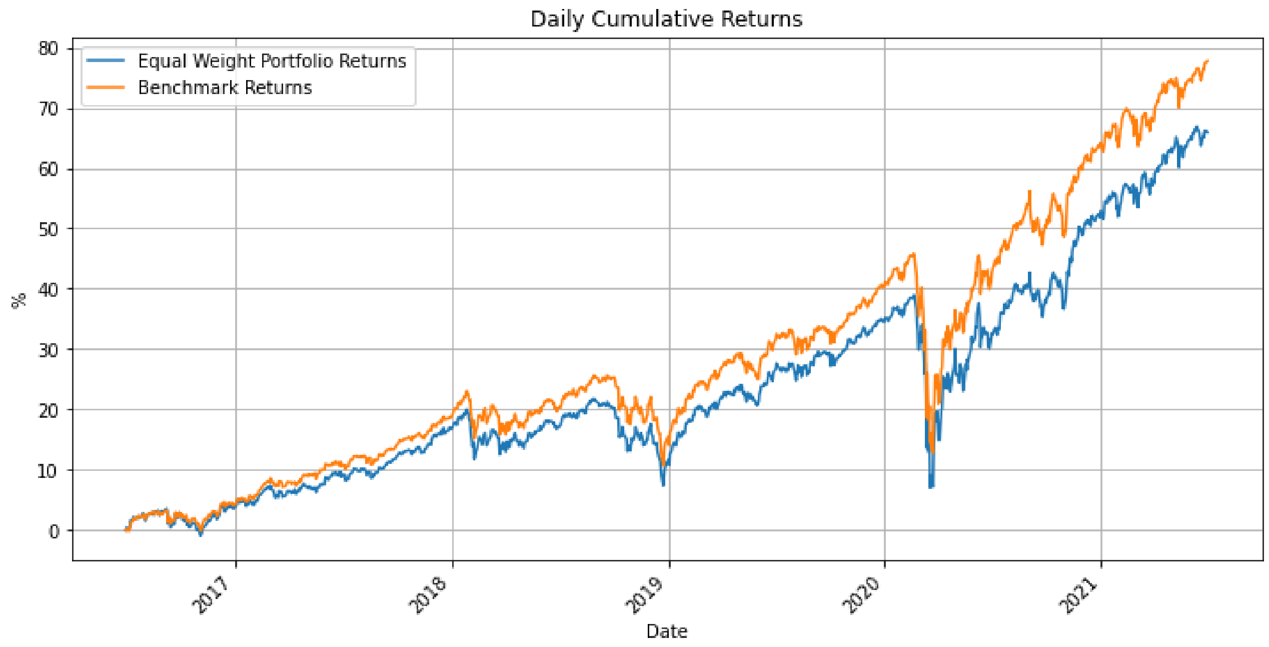
```
research_factors = pd.read_csv('data/F-F_Research_Data_Factors_daily.CSV', index
factors_df = research_factors[START:END]  # filter rows by backtest dates

# convert the annualized risk-free rate of return (average over backtest lifetim
RISK_FREE_RATE = factors_df['RF'].mean()/252
print('RISK_FREE_RATE = {:.5f}%'. format(RISK_FREE_RATE * 100))
```

```
RISK_FREE_RATE = 0.00165%
```

Organizing Data, Building Benchmark & Portfolio, Determining Cumulative Returns

In [4]:

```
# get daily returns and change col names
df_pct_change = df_adj_close.pct_change().fillna(0)
df_pct_change.columns = [col.replace(' Adj Close', ' Returns') for col in df_pct

# call it df_D, D for Daily
df_D = df_pct_change

# create an equal weight portfolio that is rebalanced daily @ market close.
df_D['Equal Weight Portfolio Returns'] = df_D[[
    'TLT Returns',
    'VTI Returns',
    'VTV Returns',
    'VBR Returns',
    'AGG Returns'
]].mean(axis='columns')

# create a 60/40 benchmark to compare portfolio returns against through out anal
df_D['Benchmark Returns'] = (
    (0.6 * df_D['VTI Returns']) + (0.4 * df_D['AGG Returns'])
)
# df_D['Benchmark Returns'] = (df_D['SPY Returns'])

# visualize the portfolio v benchmark
(((1+df_D[['Equal Weight Portfolio Returns', 'Benchmark Returns']]).cumprod()-1)
    figsize=(12,6),
    title='Daily Cumulative Returns'
)
plt.ylabel('%')
plt.grid()
plt.xticks(rotation=45)
plt.show()
portfolio_cumulative_return = round(((1+df_D['Equal Weight Portfolio Returns']).
print(f'Portfolio Cumulative Returns: {portfolio_cumulative_return}%')
benchmark_cumulative_return = round(((1+df_D['Benchmark Returns']).cumprod()[-1]
print(f'Benchmark Cumulative Returns: {benchmark_cumulative_return}%')
```

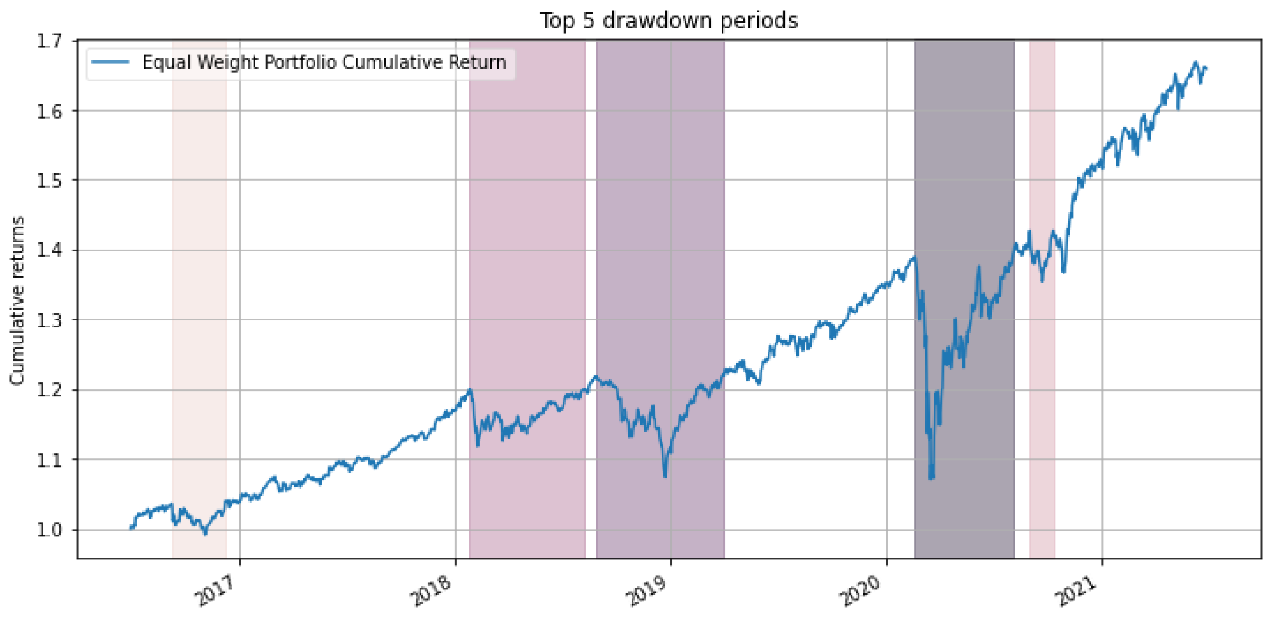


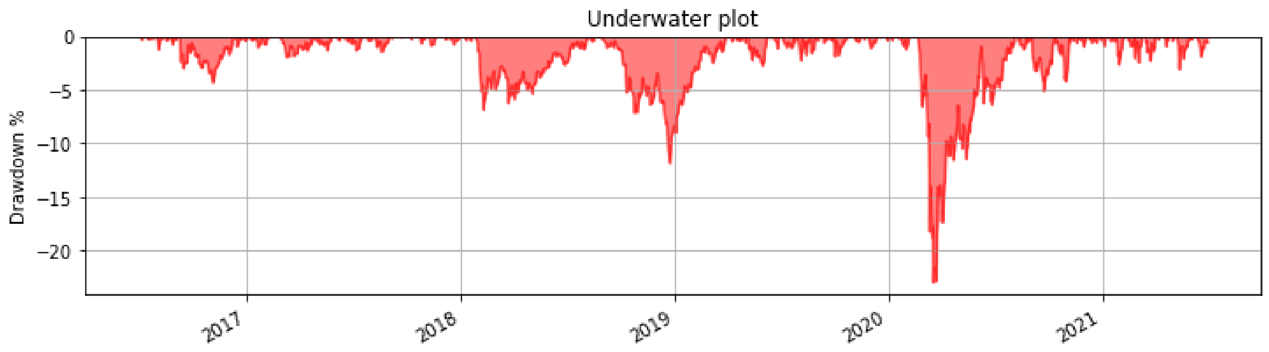
```
Portfolio Cumulative Returns: 65.88%
Benchmark Cumulative Returns: 77.73%
```

Drawdown Analysis

Here I identify the portfolio's top 5 drawdown periods and provide an underwater visualization of returns.

In [5]:
```
plt_u.plot_drawdown_periods(df_D['Equal Weight Portfolio Returns'])
plt_u.plot_drawdown_underwater(df_D['Equal Weight Portfolio Returns'])
```





Construct Bubble Portfolio

Is it possible to avoid the large drawdowns discovered in the drawdown analysis? Here we use the Log-Periodic Power Law Singularity (LPPLS) Model. It describes a bubble as a faster-than-exponential increase in asset price that reflects positive feedback loop of higher return anticipations competing with negative feedback spirals of crash expectations. A bubble has a distinct signature that resembles a power law with a finite-time singularity decorated by oscillations with a frequency increasing with time.

If we can identify bubbles in an equity benchmark, perhaps we could use that as a signal to weight our portfolio more heavily towards the less risky debt assets (AGG and TLT).

The first step is to compute the bubble indicators for the benchmark. Here I'm going to find bubbles in the VTI instrument, since it is total market.

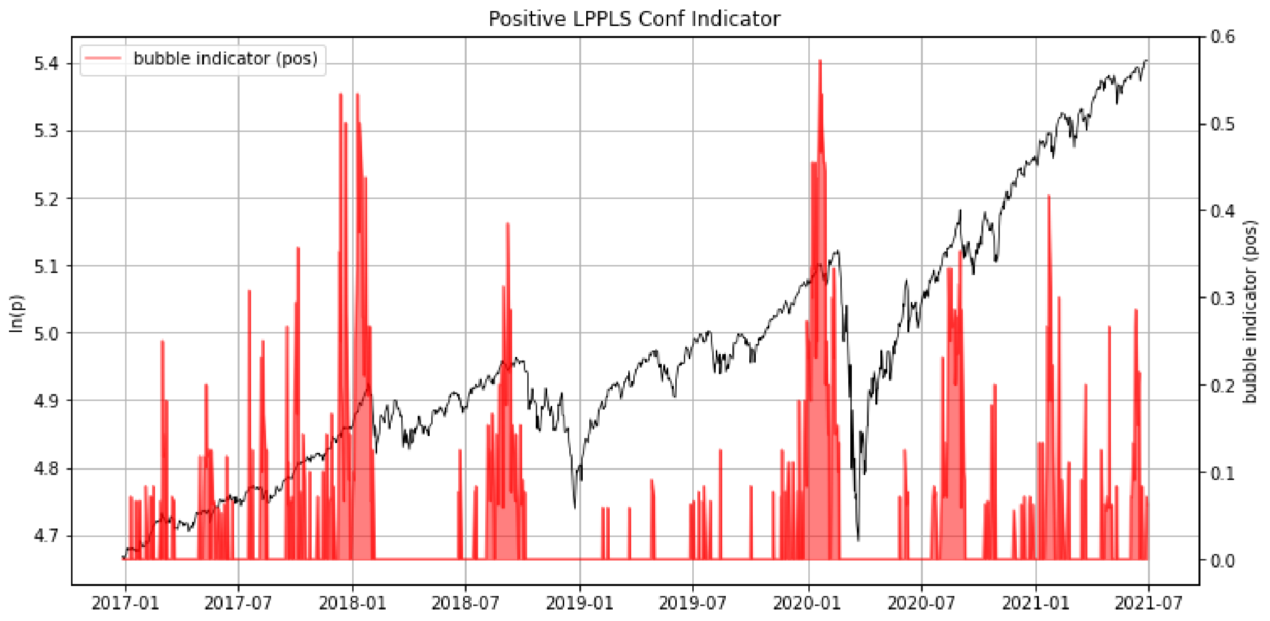
In [6]:

```
# convert Date to ordinal, that's what the LPPLS model wants - it's a neat trick
time_ord = [pd.Timestamp.toordinal(t1) for t1 in df_adj_close.index]

# create list of observation data
price = np.log(df_adj_close['VTI Adj Close'].values)

# create observations array (expected format for LPPLS observations)
observations = np.array([time_ord, price])

# set the max number for searches to perform before giving-up
# the literature suggests 25
MAX_SEARCHES = 25

# instantiate a new LPPLS model with the VTI data
lppls_model = lppls.LPPLS(observations=observations)
```

In [7]:

```
# compute the indicators and cache the result
if not exists(LPPLS_CONF_CSV):
    print('compute LPPLS conf scores fresh')
    # compute the confidence indicator
    res = lppls_model.mp_compute_nested_fits(
        workers=CPU_CORES,
        window_size=126,
        smallest_window_size=21,
        outer_increment=1,
        inner_increment=5,
        max_searches=25,
        # filter_conditions_config={} # not implemented in 0.6.x
    )
    res_df = lppls_model.compute_indicators(res)
    res_df['time'] = [pd.Timestamp.fromordinal(int(t1)) for t1 in res_df['time']
    res_df.set_index('time', inplace=True)
    res_df.to_csv(LPPLS_CONF_CSV)
else:
    print('load LPPLS conf scores from cache')
    res_df = pd.read_csv(LPPLS_CONF_CSV, index_col='time', parse_dates=True)

# visualize the conf indicator
plt_u.plot_pos_confidence_indicators(res_df)
```

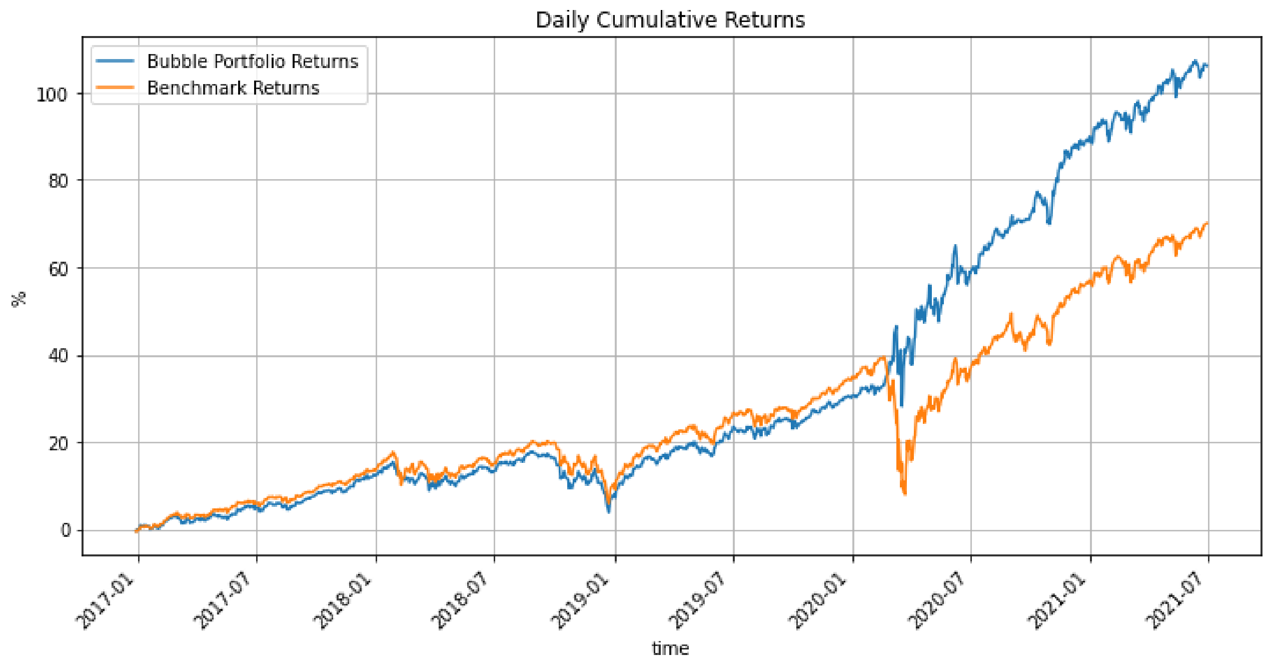
```
load LPPLS conf scores from cache
```



Next we want to use this info to weight our portfolio. A simple rule could be to reduce equity exposure to 0% across the entire portfolio when the bubble confidence indicator exceeds a threshold.

In [8]:

```
pos_conf_df = res_df.drop(['price','neg_conf', '_fits'], axis=1)
bubble_portfolio_df = pos_conf_df.join(df_D)

# prevent lookahead bias: use yesterday's conf score today
bubble_portfolio_df['pos_conf'] = bubble_portfolio_df['pos_conf'].shift(1)

# group pos_conf by month and take the mean,
# @TODO: it would be better to weight most recent observations heavier
pos_conf_M = bubble_portfolio_df['pos_conf'].groupby(pd.Grouper(freq='M')).mean(

# reintegrate monthly data to bubble_portfolio_df and forward fill the indicator
# the previous month's mean pos_conf will determine what we do all next month
bp_df = bubble_portfolio_df.join(pos_conf_M.rename('pos_conf_M', inplace=True))
bp_df['pos_conf_M'] = bp_df['pos_conf_M'].fillna(method='ffill').fillna(0)

# construct a new portfolio with bubble weights...
conditions = [(bp_df['pos_conf_M'] > BUBBLE_THRESHOLD), (bp_df['pos_conf_M'] <=
values = [
    (   # ⬇️ This is the bubble portfolio
        (0.0 * bp_df['VTI Returns']) \
        + (0.0 * bp_df['VTV Returns']) \
        + (0.0 * bp_df['VBR Returns']) \
        + (0.5 * bp_df['AGG Returns']) \
        + (0.5 * bp_df['TLT Returns']) \
    ),( # ⬇️ This is the equal weight portfolio
        (0.2 * bp_df['VTI Returns']) \
        + (0.2 * bp_df['VTV Returns']) \
        + (0.2 * bp_df['VBR Returns']) \
        + (0.2 * bp_df['AGG Returns']) \
        + (0.2 * bp_df['TLT Returns']) \
    )
]
bp_df['Bubble Portfolio Returns'] = np.select(conditions, values)

# visualize the portfolio v benchmark
(((1+bp_df[['Bubble Portfolio Returns', 'Benchmark Returns']]).cumprod()-1)*100)
    figsize=(12,6),
    title='Daily Cumulative Returns'
)
plt.ylabel('%')
plt.grid()
plt.xticks(rotation=45)
plt.show()
portfolio_cumulative_return = round(((1+bp_df['Bubble Portfolio Returns']).cumpr
print(f'Bubble Portfolio Cumulative Returns: {portfolio_cumulative_return}%')
benchmark_cumulative_return = round(((1+bp_df['Benchmark Returns']).cumprod()[-1
print(f'Benchmark Cumulative Returns: {benchmark_cumulative_return}%')
```

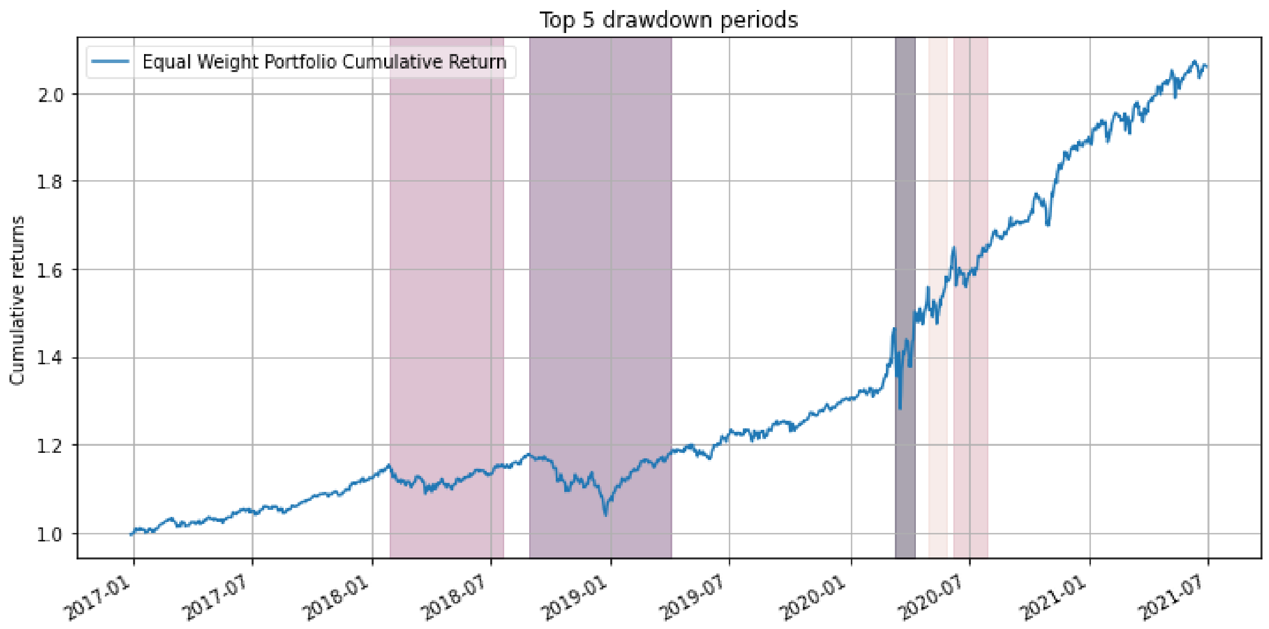


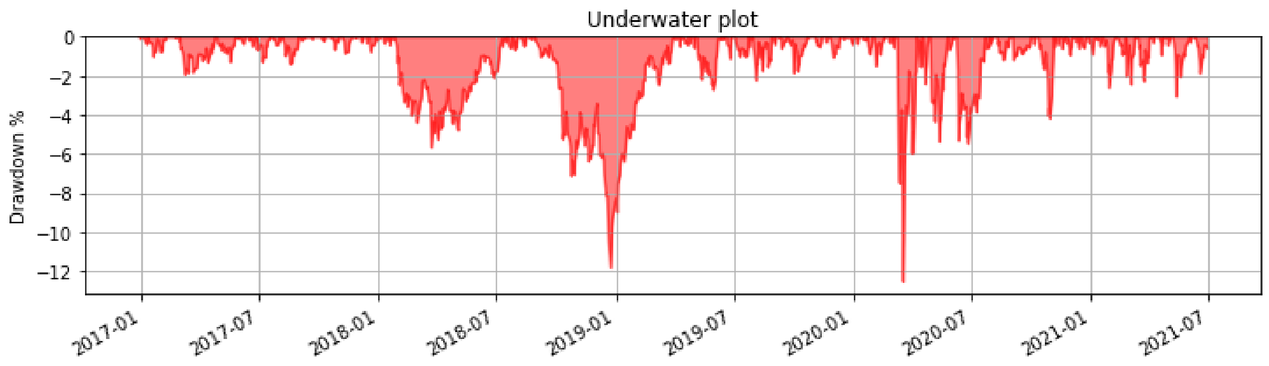
```
Bubble Portfolio Cumulative Returns: 106.07%
Benchmark Cumulative Returns: 69.97%
```

Nice! We now outperform the benchmark and we were able to partially avoid the largest drawdown! Avoiding this drawdown is fascinating because the bubble indicator, which only operates on historical price data (i.e., endogenous data), seems to be able to predict the COVID crash of February 2020 - a seemingly exogenous event. I recall a preprint that looked at this issue specifically: https://arxiv.org/pdf/2101.03625.pdf. Their finding was that the crash could mostly be described endogenously, which is quiet counterintuitive. Nonetheless, our backtest seems to corroborate this. Neat.

Below are the new drawdown stats for the bubble portfolio. The max drawdown was reduced from ~26% to ~12%.

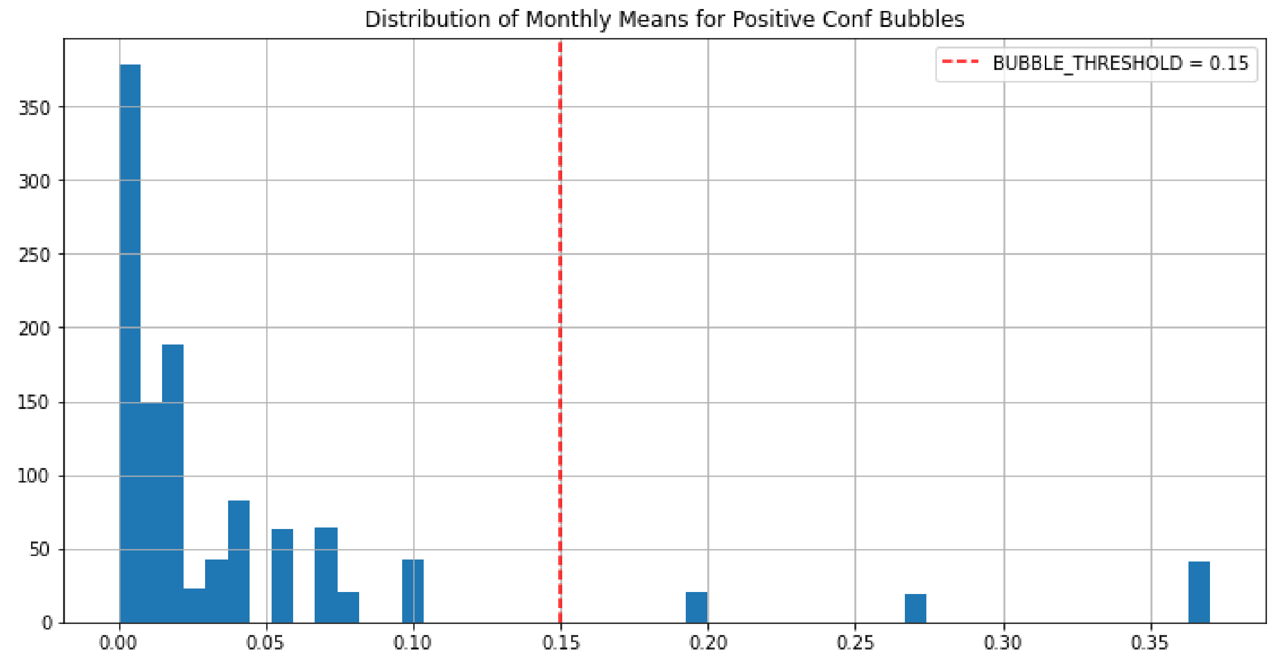
In [9]:
```
plt_u.plot_drawdown_periods(bp_df['Bubble Portfolio Returns'])
plt_u.plot_drawdown_underwater(bp_df['Bubble Portfolio Returns'])
```





If we wanted to, we could try to optimize the bubble threshold value by looking at the distribution of values.

In [10]:
```
plt.figure(figsize=(12,6))
plt.hist(bp_df['pos_conf_M'], bins=50)
plt.axvline(BUBBLE_THRESHOLD, color='red', ls='--', label=f'BUBBLE_THRESHOLD = {
plt.title('Distribution of Monthly Means for Positive Conf Bubbles')
plt.legend()
plt.grid()
plt.show()
```



Backtest Performance Summary Statistics

Below I compute a few performance metrics for the entire backtest period and for a rolling 6 month window.

Sharpe

$$Sharpe = \frac{R_p - R_f}{\sigma_p}$$

where

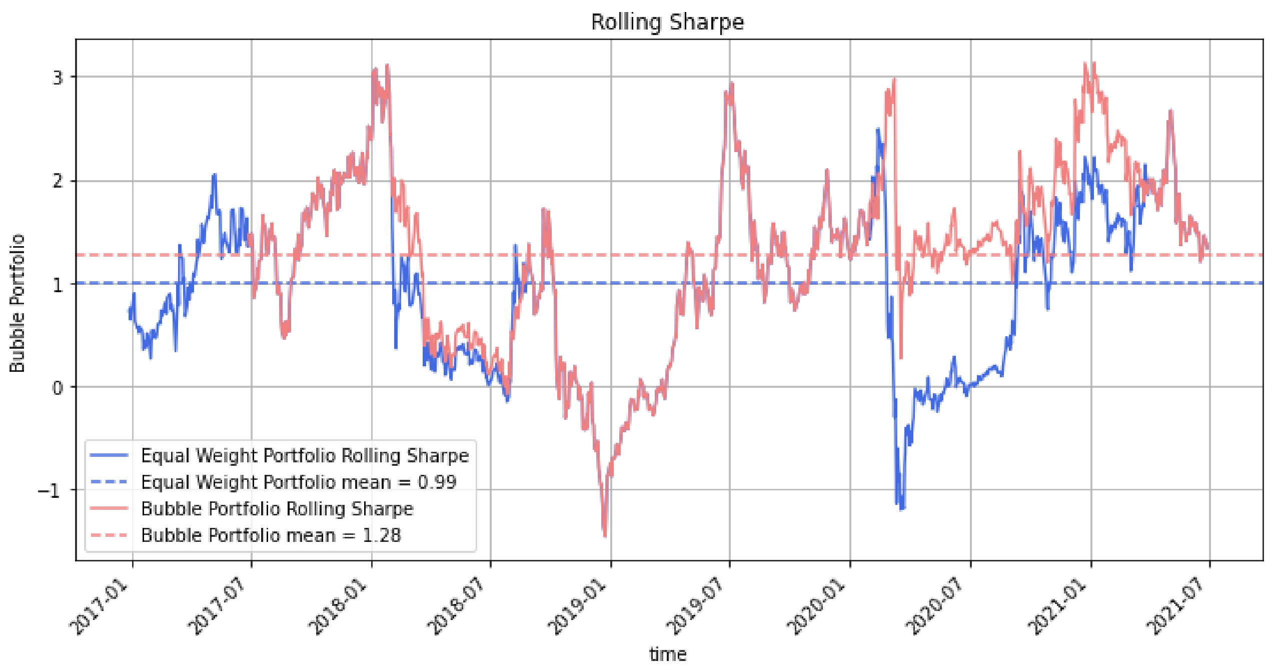
- $R_p =$ return of portfolio
- $R_f =$ risk-free rate
- $\sigma_p =$ standard deviation of the portfolio's excess return

In [11]:

```
plt_u.plot_sharpe([
    (
        df_D['Equal Weight Portfolio Returns'],
        RISK_FREE_RATE,
        df_D['Equal Weight Portfolio Returns'].std(),
        'Equal Weight Portfolio',
        'royalblue',
    ), (
        bp_df['Bubble Portfolio Returns'],
        RISK_FREE_RATE,
        bp_df['Bubble Portfolio Returns'].std(),
        'Bubble Portfolio',
        'lightcoral',
    )
])
```

```
Equal Weight Portfolio Sharpe Ratio (Since Inception): 0.91
```

```
Bubble Portfolio Sharpe Ratio (Since Inception): 1.59
```



Sortino Ratio

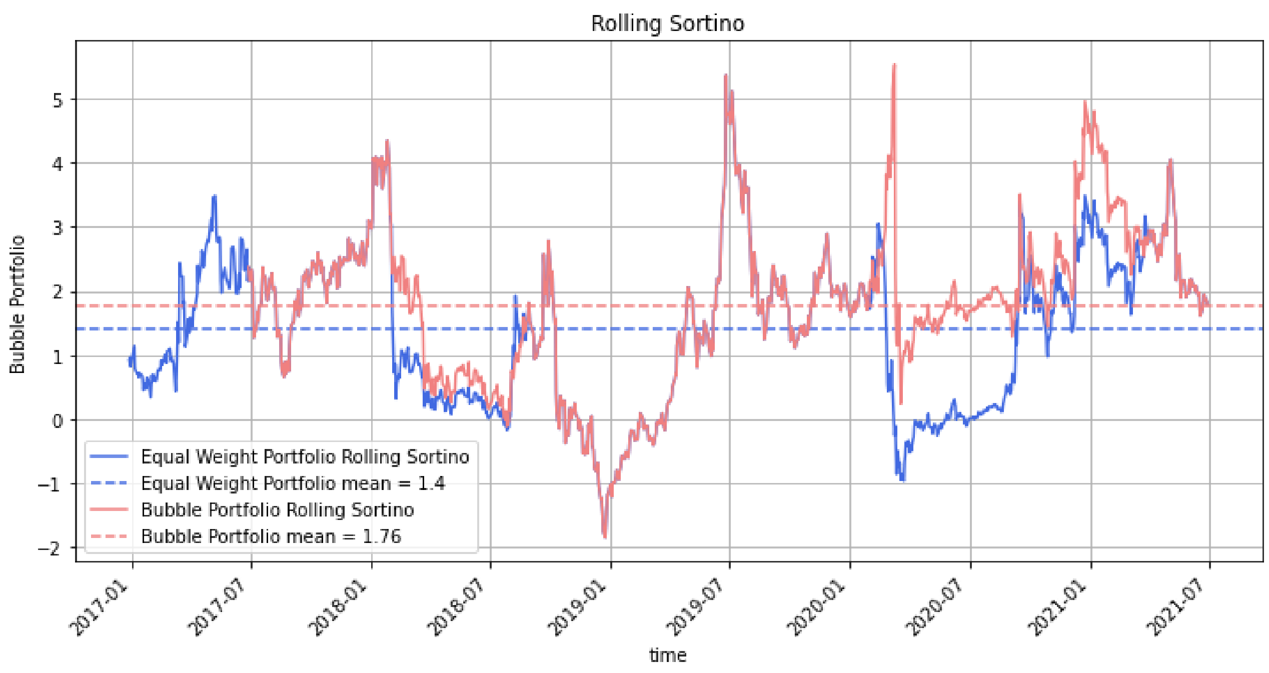
$$Sortino = \frac{R_p - R_f}{\sigma_d}$$

where

- R_p = return of portfolio
- R_f = risk-free rate
- σ_d = standard deviation of the downside

In [12]:
```
plt_u.plot_sortino([
    (
        df_D['Equal Weight Portfolio Returns'],
        RISK_FREE_RATE,
        (df_D['Equal Weight Portfolio Returns'][df_D['Equal Weight Portfolio Ret
        'Equal Weight Portfolio',
        'royalblue',
    ),
    (
        bp_df['Bubble Portfolio Returns'],
        RISK_FREE_RATE,
        (bp_df['Bubble Portfolio Returns'][bp_df['Bubble Portfolio Returns'] < 0
        'Bubble Portfolio',
        'lightcoral'
    )
])
```

```
Equal Weight Portfolio Sortino Ratio (Since Inception): 0.96
Bubble Portfolio Sortino Ratio (Since Inception): 1.93
```



Information Ratio

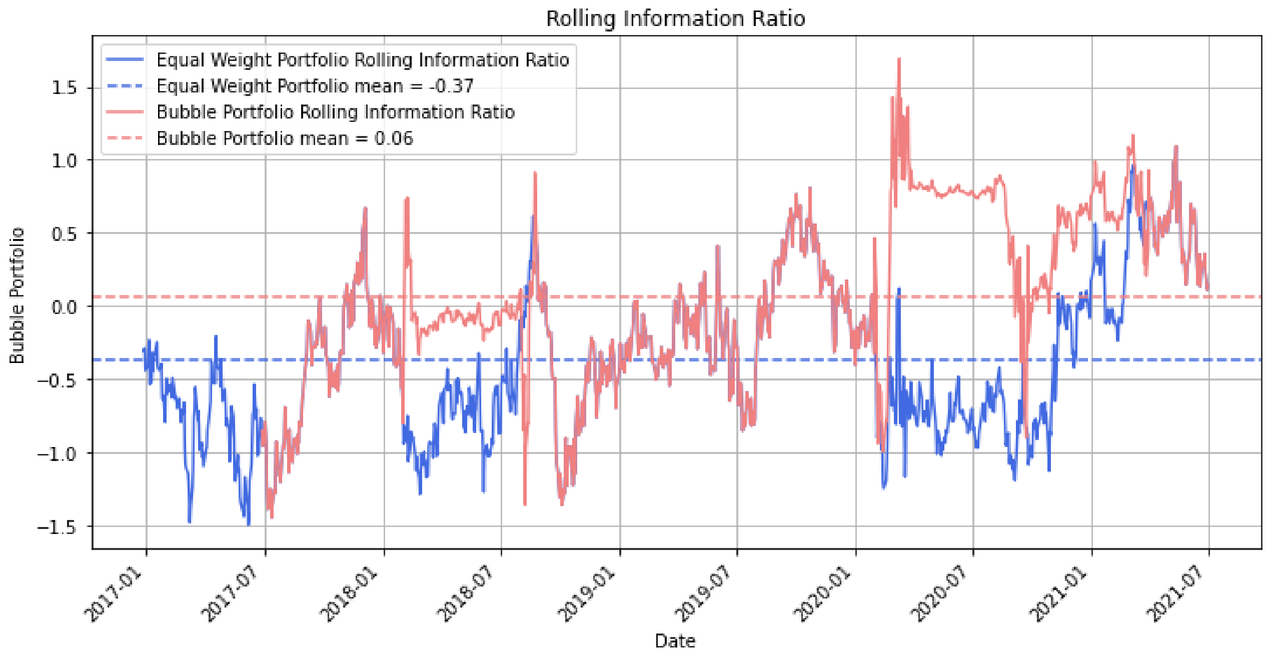
$IR = \frac{R_p - R_b}{\sigma_p}$

where

- R_p = return of portfolio
- R_b = return of a benchmark portfolio
- σ_p = standard deviation of the portfolio's excess return

In [13]:
```
plt_u.plot_ir([
    (
        df_D['Equal Weight Portfolio Returns'],
        df_D['Benchmark Returns'],
        'Equal Weight Portfolio',
        'royalblue',
    ),
    (
        bp_df['Bubble Portfolio Returns'],
        df_D['Benchmark Returns'],
        'Bubble Portfolio',
        'lightcoral'
    )
])
```

```
Equal Weight Portfolio Information Ratio (Since Inception): -0.45
Bubble Portfolio Information Ratio (Since Inception): 0.36
```



Beta

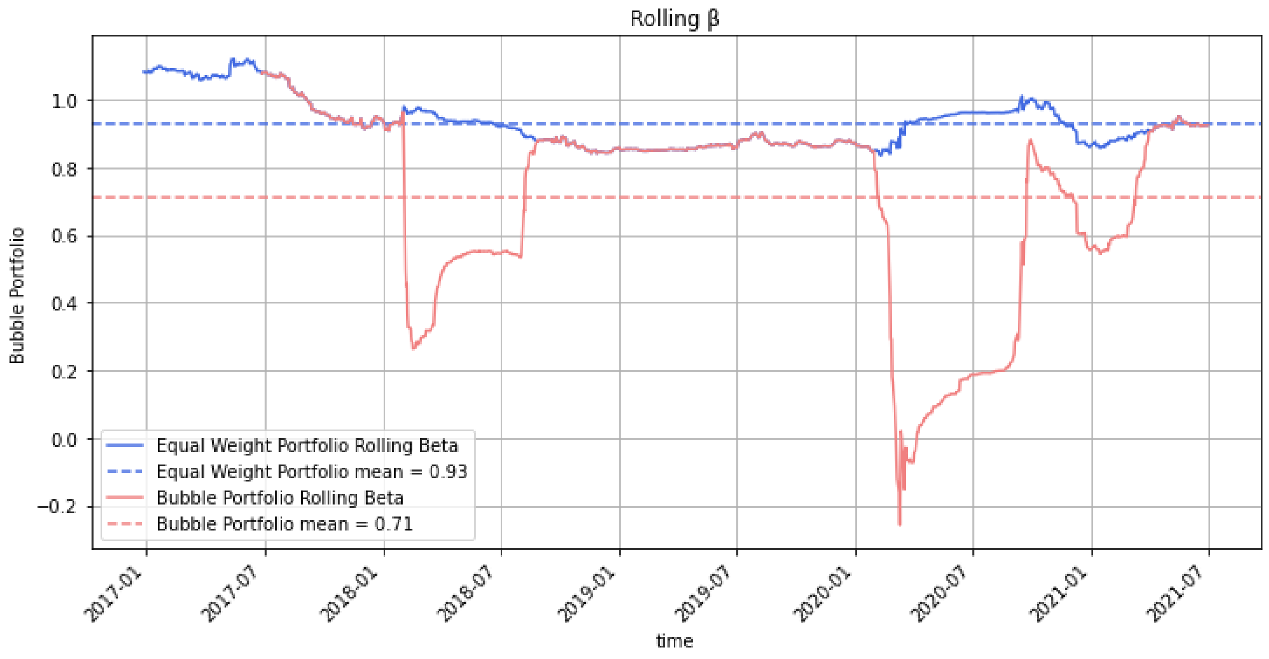
$$\beta = \frac{Cov(R_p, R_b)}{Var(R_m)}$$

where

- $R_p =$ return of portfolio
- $R_b =$ return of a benchmark portfolio

In [14]:
```
plt_u.plot_beta([
    (
        df_D[['Equal Weight Portfolio Returns', 'Benchmark Returns']],
        df_D['Equal Weight Portfolio Returns'],
        df_D['Benchmark Returns'],
        'Equal Weight Portfolio',
        'royalblue'
    ),
    (
        bp_df[['Bubble Portfolio Returns', 'Benchmark Returns']],
        bp_df['Bubble Portfolio Returns'],
        bp_df['Benchmark Returns'],
        'Bubble Portfolio',
        'lightcoral'
    )
])
```

```
Equal Weight Portfolio Beta (Since Inception): 0.94
Bubble Portfolio Beta (Since Inception): 0.41
```



Conclusion

This methodology could be used in conjunction with various asset allocation models. It effictively avoids large markets drawdowns. You should incorporate it in your fund or portfolio, hmu.

```
In [ ]:
```