In [1]:
```
import yfinance as yf
import datetime
import numpy as np
import matplotlib.pyplot as plt
import hvplot.pandas
import pandas as pd
import quantstats as qs
import talib as ta
```

In [2]:
```
df = yf.download("BTC-USD")
```

```
[*********************100%***********************]  1 of 1 completed
```

In [3]:
```
df.tail(15)
```

Out[3]:

Date	Open	High	Low	Close	Adj Close	Volume
2022-05-26	29564.777344	29834.160156	28261.906250	29267.224609	29267.224609	36774325352
2022-05-27	29251.140625	29346.943359	28326.613281	28627.574219	28627.574219	36582005748
2022-05-28	28622.625000	28814.900391	28554.566406	28814.900391	28814.900391	35519577634
2022-05-29	29019.867188	29498.009766	28841.107422	29445.957031	29445.957031	18093886409
2022-05-30	29443.365234	31949.630859	29303.572266	31726.390625	31726.390625	39277993274
2022-05-31	31723.865234	32249.863281	31286.154297	31792.310547	31792.310547	33538210634
2022-06-01	31792.554688	31957.285156	29501.587891	29799.080078	29799.080078	41135817341
2022-06-02	29794.890625	30604.734375	29652.705078	30467.488281	30467.488281	29083562061
2022-06-03	30467.806641	30633.035156	29375.689453	29704.390625	29704.390625	26175547452
2022-06-04	29706.138672	29930.564453	29500.005859	29832.914062	29832.914062	16588370958
2022-06-05	29835.117188	30117.744141	29574.449219	29906.662109	29906.662109	17264085441

Date	Open	High	Low	Close	Adj Close	Volume
2022-06-06	29910.283203	31693.291016	29894.187500	31370.671875	31370.671875	31947336829
2022-06-07	31371.742188	31489.683594	29311.683594	31155.478516	31155.478516	40770974039
2022-06-08	31151.480469	31253.691406	29944.404297	30214.355469	30214.355469	30242059107
2022-06-09	30177.673828	30435.257812	30088.888672	30435.257812	30435.257812	23960582144

In [4]:

```
# Count nulls
df.isna().sum()
```

Out[4]:

```
Open         0
High         0
Low          0
Close        0
Adj Close    0
Volume       0
dtype: int64
```

In [5]:

```
# Calculate VWAP
df["VWAP"] = (df.Volume*(df.Close)).cumsum() / df.Volume.cumsum()
```

In [6]:

```
df.head()
```

Out[6]:

Date	Open	High	Low	Close	Adj Close	Volume	VWAP
2014-09-17	465.864014	468.174011	452.421997	457.334015	457.334015	21056800	457.334015
2014-09-18	456.859985	456.859985	413.104004	424.440002	424.440002	34483200	436.911062
2014-09-19	424.102997	427.834991	384.532013	394.795990	394.795990	37919700	419.823580
2014-09-20	394.673004	423.295990	389.882996	408.903992	408.903992	36863600	416.734836
2014-09-21	408.084991	412.425995	393.181000	398.821014	398.821014	26580100	413.700159

In [7]:

```
# Drop coulmns
df.drop(columns=["Adj Close", "Volume"])
```

Out[7]:

	Open	High	Low	Close	VWAP
Date					
2014-09-17	465.864014	468.174011	452.421997	457.334015	457.334015
2014-09-18	456.859985	456.859985	413.104004	424.440002	436.911062
2014-09-19	424.102997	427.834991	384.532013	394.795990	419.823580
2014-09-20	394.673004	423.295990	389.882996	408.903992	416.734836
2014-09-21	408.084991	412.425995	393.181000	398.821014	413.700159
...	...	...	...	...	...
2022-06-05	29835.117188	30117.744141	29574.449219	29906.662109	28017.143538
2022-06-06	29910.283203	31693.291016	29894.187500	31370.671875	28019.631692
2022-06-07	31371.742188	31489.683594	29311.683594	31155.478516	28022.598132
2022-06-08	31151.480469	31253.691406	29944.404297	30214.355469	28024.134972
2022-06-09	30177.673828	30435.257812	30088.888672	30435.257812	28025.473725

2823 rows × 5 columns

In [8]:

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
DatetimeIndex: 2823 entries, 2014-09-17 to 2022-06-09
Data columns (total 7 columns):
 #   Column     Non-Null Count  Dtype  
---  ------     --------------  -----  
 0   Open       2823 non-null   float64
 1   High       2823 non-null   float64
 2   Low        2823 non-null   float64
 3   Close      2823 non-null   float64
 4   Adj Close  2823 non-null   float64
```

```
 5   Volume     2823 non-null   int64
 6   VWAP       2823 non-null   float64
dtypes: float64(6), int64(1)
memory usage: 176.4 KB
```

In [9]:

```
# Convert to datetime index
df.index = pd.to_datetime(df.index)
```

In [10]:

```
df.Close.plot(figsize=(16, 8))
plt.ylabel("BTCUSD Price")
plt.show()
```

In [11]:

```
# Tenkansen (Conversion Line)
high_9 = df.High.rolling(9).max()
low_9 = df.Low.rolling(9).min()
df["conversion_line"] = (high_9 + low_9) / 2
conversion_line = df[["Close", "conversion_line"]]
conversion_line[-600:].plot(figsize=(16, 8))
plt.legend(loc="center right", bbox_to_anchor=(1.3, 0.5))
plt.ylabel("BTCUSD Price")
plt.show()
```

In [12]:

```
# Kijun-sen (Base Line)
high_26 = df.High.rolling(26).max()
low_26 = df.Low.rolling(26).min()
df["base_line"] = (high_26 + low_26) / 2

base_line = df[["Close", "conversion_line", "base_line"]]
base_line[-600:].plot(figsize=(16, 8))
```

```
plt.legend(loc="center right", bbox_to_anchor=(1.3, 0.5))
plt.ylabel("BTCUSD Price")
plt.show()
```

In [13]:

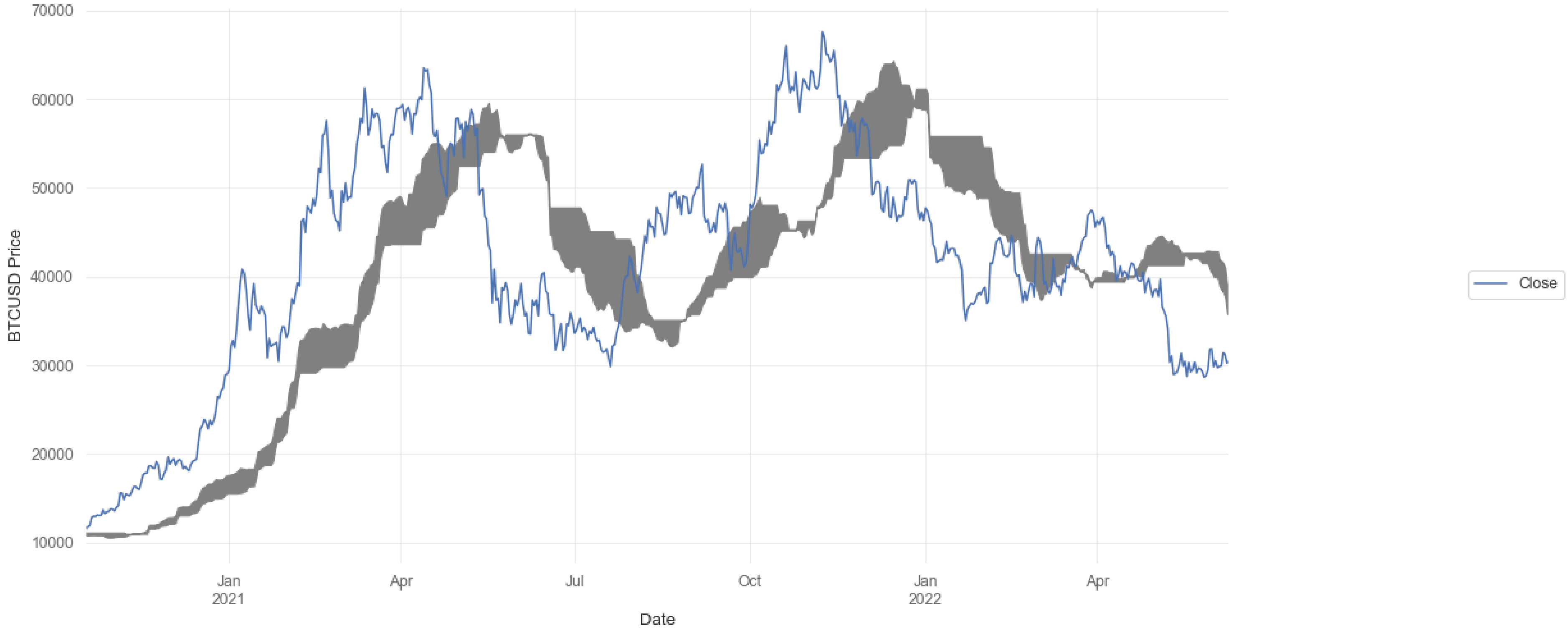
```
# Senkou Span A (Leading Span A)
df["leading_span_A"] = ((df.conversion_line + df.base_line) / 2).shift(30)

leading_span_A = df[["Close", "conversion_line",
                     "base_line", "leading_span_A"]]

leading_span_A[-600:].plot(figsize=(16, 8))
plt.legend(loc="center right", bbox_to_anchor=(1.3, 0.5))
plt.ylabel("BTCUSD Price")
plt.show()
```

In [14]:

```
# Senkou Span B (Leading Span B)
high_52 = df.High.rolling(52).max()
low_52 = df.Low.rolling(52).min()
df["leading_span_B"] = ((high_52 + low_52) / 2).shift(30)

leading_span_B = df[["Close", "conversion_line",
                     "base_line", "leading_span_A", "leading_span_B"]]
leading_span_B[-600:].plot(figsize=(16, 8))
plt.legend(loc="center right", bbox_to_anchor=(1.3, 0.5))
plt.ylabel("BTCUSD Price")
plt.show()
```

In [15]:

```
# Ichimoku Cloud
cloud = df[-600:].Close.plot(figsize=(16, 8))
cloud.fill_between(
    df[-600:].index, df[-600:].leading_span_A, df[-600:].leading_span_B, color="grey")
plt.legend(loc="center right", bbox_to_anchor=(1.3, 0.5))
plt.ylabel("BTCUSD Price")
plt.show()
```



In [16]:

```
# RSI indicator settings
df['RSI'] = ta.RSI(df.Close,14)
```

In [17]:

```
# Entry setup
df["signal"] = np.nan

# Prices are above the cloud
condition_1 = (df.Close > df.leading_span_A) & (df.Close > df.leading_span_B)

# Leading Span A (senkou_span_A) is greater than Leading span B (senkou_span_B)
condition_2 = (df.leading_span_A > df.leading_span_B)

# # Conversion Line (tenkan_sen) moves above Base Line (kijun_sen)
condition_3 = (df.conversion_line > df.base_line)

# RSI momentum
condition_4 = (df.RSI > 50)
```

```python
# Combine the conditions and store in the signal column 1 when all the conditions are true
df.loc[condition_1 & condition_2 & condition_3 & condition_4, "signal"] = 1
```

In [18]:

```python
# Exit (to cash)
# Price closes below the cloud
condition_1 = (df.Close < df.leading_span_A)

# Store condition in signal column 0 when true
df.loc[(condition_1), "signal"] = 0

# If signal NA foward fill with previous signal
df.signal.fillna(method="ffill", inplace=True)

df.iloc[320:360, :]
```

Out[18]:

Date	Open	High	Low	Close	Adj Close	Volume	VWAP	conversion_line	base_line	leading_span_A	leading_span_B	
2015-08-03	282.806000	285.471008	280.233002	281.226990	281.226990	21474100	286.633870	287.651489	290.740005	251.304001	244.581505	51.1
2015-08-04	281.225006	285.714996	281.225006	285.217987	285.217987	21908700	286.630108	287.651489	291.598007	255.034756	247.901009	54.9
2015-08-05	284.846985	285.501007	281.488007	281.881989	281.881989	20128000	286.618547	287.088989	293.218506	257.761250	249.359001	51.3
2015-08-06	281.906006	281.906006	278.403015	278.576996	278.576996	18792100	286.600308	286.032501	293.218506	258.158749	249.359001	47.9
2015-08-07	278.740997	280.391998	276.365997	279.584991	279.584991	42484800	286.564519	283.246002	291.495499	259.389751	249.359001	49.0
2015-08-08	279.742004	279.928009	260.709991	260.997009	260.997009	58533000	286.386068	274.834503	279.241989	260.088249	249.359001	34.6
2015-08-09	261.115997	267.002991	260.467987	265.083008	265.083008	23789600	286.325808	273.091492	279.120987	269.027252	257.943504	38.8
2015-08-10	265.477997	267.032013	262.596008	264.470001	264.470001	20979400	286.271423	273.091492	279.120987	271.659756	259.901009	38.4

Date	Open	High	Low	Close	Adj Close	Volume	VWAP	conversion_line	base_line	leading_span_A	leading_span_B	
2015-08-11	264.342010	270.385986	264.093994	270.385986	270.385986	25433900	286.223646	273.091492	279.120987	280.838257	267.845009	44.
2015-08-12	270.597992	270.673004	265.468994	266.376007	266.376007	26815400	286.160909	273.091492	279.120987	281.963505	267.845009	41.
2015-08-13	266.183014	266.231995	262.841003	264.079987	264.079987	27685500	286.089082	272.984497	279.120987	283.384754	267.845009	39.
2015-08-14	264.131989	267.466003	261.477997	265.679993	265.679993	27091200	286.024324	271.186996	279.120987	283.384754	267.845009	41.
2015-08-15	265.528992	266.666992	261.295990	261.550995	261.550995	19321100	285.969068	270.429993	279.120987	283.384754	267.845009	38.
2015-08-16	261.865997	262.440002	257.040985	258.506989	258.506989	29717000	285.874031	268.484497	277.407486	284.059757	267.845009	36.
2015-08-17	258.489990	260.505005	257.117004	257.976013	257.976013	21617900	285.803975	263.856995	277.407486	284.488758	267.845009	36.
2015-08-18	257.925995	257.993011	211.078995	211.078995	211.078995	42147200	285.439916	240.875999	254.426491	285.299007	267.845009	18.
2015-08-19	225.671005	237.408997	222.766006	226.684006	226.684006	60869200	285.029388	240.875999	254.426491	285.299007	267.845009	30.
2015-08-20	226.899002	237.365005	226.899002	235.350006	235.350006	32275000	284.846017	240.875999	254.426491	284.734501	267.845009	36.
2015-08-21	235.354996	236.432007	231.723999	232.569000	232.569000	23173800	284.707837	239.272499	254.426491	281.425255	267.845009	35.
2015-08-22	232.662003	234.957001	222.703995	230.389999	230.389999	23205900	284.564443	239.272499	253.863991	281.779751	268.406509	34.
2015-08-23	230.376007	232.705002	225.580002	228.169006	228.169006	18406600	284.446602	238.872993	252.807503	281.550255	268.523003	33.
2015-08-24	228.112000	228.139008	210.442993	210.494995	210.494995	59220700	283.952755	236.441498	250.284500	282.668755	268.523003	27.

Date	Open	High	Low	Close	Adj Close	Volume	VWAP	conversion_line	base_line	leading_span_A	leading_span_B	
2015-08-25	210.067993	226.320999	199.567001	221.608994	221.608994	61089200	283.526227	230.036003	244.263008	283.366005	268.523003	35.3
2015-08-26	222.076004	231.182999	220.203995	225.830994	225.830994	31808000	283.321431	228.780006	242.640999	284.546501	268.523003	38.0
2015-08-27	226.050003	228.643005	223.684006	224.768997	224.768997	21905400	283.178646	218.487999	242.640999	284.658249	268.523003	37.6
2015-08-28	224.701004	235.218994	220.925995	231.395996	231.395996	31336600	282.998631	218.466003	242.640999	285.187252	268.616508	41.9
2015-08-29	231.548996	233.222000	227.330002	229.779999	229.779999	17142500	282.897616	217.999504	242.640999	286.312500	271.161507	41.7
2015-08-30	229.895004	232.067993	226.246994	228.761002	228.761002	19412600	282.781501	217.392998	242.534004	287.951996	271.202003	40.6
2015-08-31	229.113998	231.955994	225.914993	230.056000	230.056000	20710700	282.661125	217.392998	240.736504	287.951996	271.580505	41.6
2015-09-01	230.255997	231.216003	226.860001	228.121002	228.121002	20575200	282.537701	217.392998	239.979500	288.520744	271.802010	40.5
2015-09-02	228.026993	230.576996	226.475006	229.283997	229.283997	18760400	282.428045	217.392998	239.747505	289.195747	271.802010	41.5
2015-09-03	229.324005	229.604996	226.667007	227.182999	227.182999	17482000	282.322242	227.711494	235.120003	289.624748	273.199005	40.2
2015-09-04	227.214996	230.899994	227.050995	230.298004	230.298004	20962400	282.203046	228.072495	235.120003	290.153748	273.908005	43.0
2015-09-05	230.199005	236.143005	229.442993	235.018997	235.018997	20671400	282.096681	228.534500	235.120003	289.625504	275.258003	47.0
2015-09-06	234.869995	242.912003	234.681000	239.839996	239.839996	25473700	281.979619	234.413498	235.120003	287.370750	277.379509	50.8
2015-09-07	239.934006	242.106003	238.722000	239.847000	239.847000	21192200	281.882741	234.413498	233.516502	277.038246	277.379509	50.8

Date	Open	High	Low	Close	Adj Close	Volume	VWAP	conversion_line	base_line	leading_span_A	leading_span_B	
2015-09-08	239.845993	245.781006	239.677994	243.606995	243.606995	26879200	281.771438	235.848000	233.516502	276.106239	277.379509	53.
2015-09-09	243.414993	244.416000	237.820999	238.167999	238.167999	23635700	281.660228	236.128006	233.116997	276.106239	277.379509	49.
2015-09-10	238.335999	241.292999	235.791000	238.477005	238.477005	21215500	281.561593	236.128006	231.003502	276.106239	277.379509	49.
2015-09-11	238.328995	241.169006	238.328995	240.106995	240.106995	19224700	281.475968	236.224007	230.036003	276.106239	277.379509	50.

In [19]:

```
df["signal_change"] = df.signal.diff()
df["signal_change"].value_counts()
```

Out[19]:

```
 0.0    2708
 1.0      25
-1.0      25
Name: signal_change, dtype: int64
```

In [20]:

```
# Visualize entry position relative to close price
entry = df[df["signal_change"] == 1.0]["Close"].hvplot.scatter(
    color="green",
    marker="^",
    size=200,
    legend=False,
    ylabel="Price in $",
    width=1000,
    height=400
)

# Visualize exit position relative to close price
exit = df[df["signal_change"] == -1.0]["Close"].hvplot.scatter(
    color="red",
    marker="v",
    size=200,
    legend=False,
```

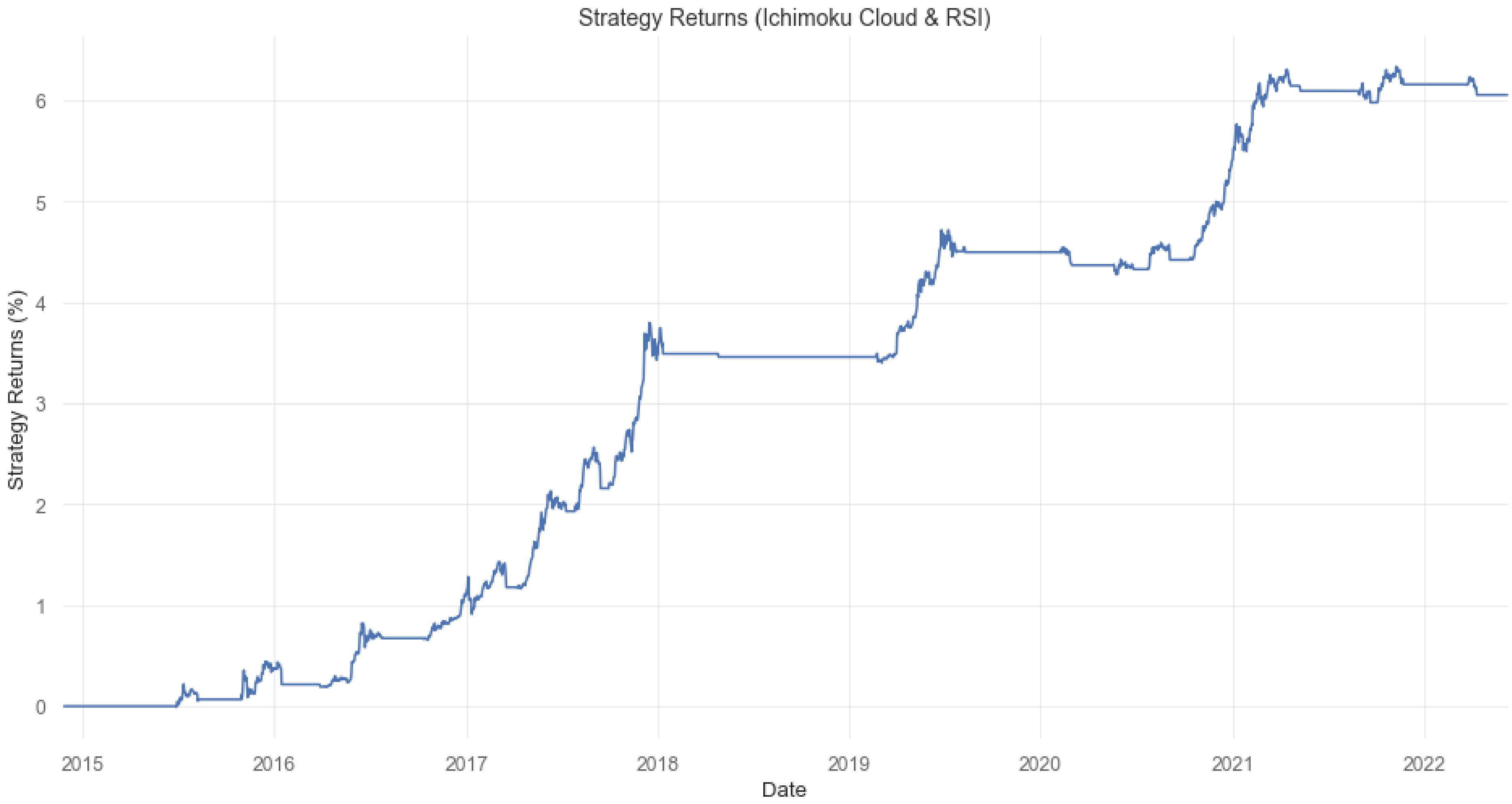
```
    ylabel="Price in $",
    width=1000,
    height=400
)


# Visualize close price for the investment
security_close = df[["Close"]].hvplot(
    line_color="lightgray",
    ylabel="Price in $",
    width=1000,
    height=400
)

# Plot Ichimoku indicators
ichi = df[["Close", "conversion_line",
                     "base_line", "leading_span_A", "leading_span_B"]].hvplot(
    ylabel="Price in $",
    width=1000,
    height=400
)


# # Overlay plots
ichiplot = security_close * ichi * entry * exit
ichiplot
```

Out[20]:

In [21]:

```
# Calculate daily returns
daily_returns = df.Close.pct_change()

# Calculate strategy returns
strategy_returns = daily_returns * df.signal.shift(1)
strategy_returns.dropna(inplace=True)

# Plot strategy returns
strategy_returns.cumsum().plot(figsize=(16, 8))
plt.xlabel("Date")
plt.ylabel("Strategy Returns (%)")
```

```
plt.title("Strategy Returns (Ichimoku Cloud & RSI)", fontsize=14)
plt.show()
```



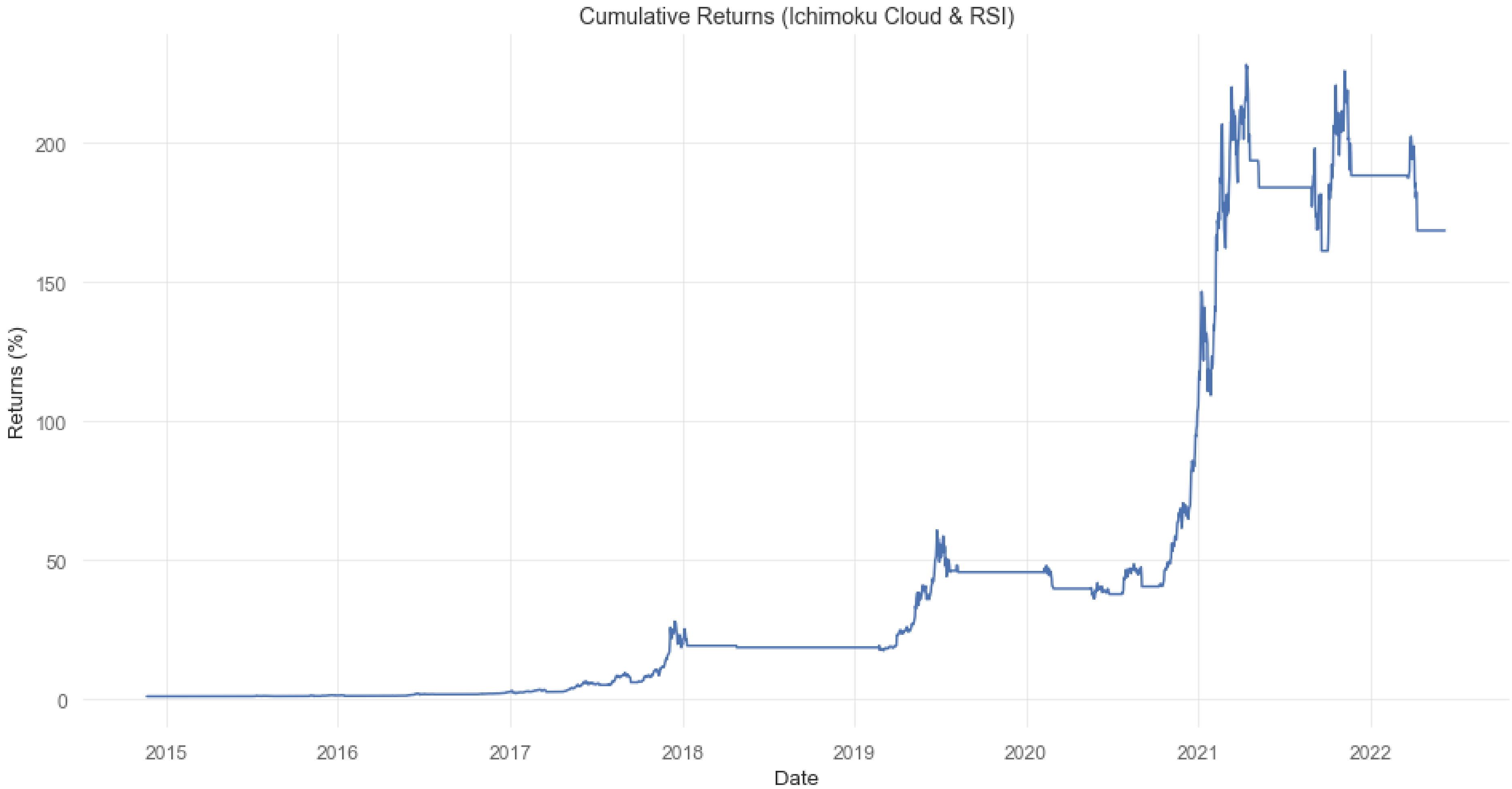
In [22]:

```
# Check Sharpe ratio calculation
def annualized_sharpe_ratio(returns, N=252):
    return ((N) * returns.mean()) / (returns.std() * np.sqrt(N))

# Sharpe ratio
excess_daily_strategy_return = strategy_returns
sharpe = annualized_sharpe_ratio(excess_daily_strategy_return)
print("The Sharpe ratio of strategy is %.2f" % sharpe)
```

```
The Sharpe ratio of strategy is 1.34
```

In [23]:

```
# Calculate the cumulative returns
df["cumulative_returns"] = (strategy_returns+1).cumprod()

# Plot the cumulative returns
plt.figure(figsize=(16, 8))
plt.plot(df["cumulative_returns"])
plt.title("Cumulative Returns (Ichimoku Cloud & RSI)", fontsize=14)
plt.xlabel("Date")
plt.ylabel("Returns (%)")
plt.show()
```



In [24]:

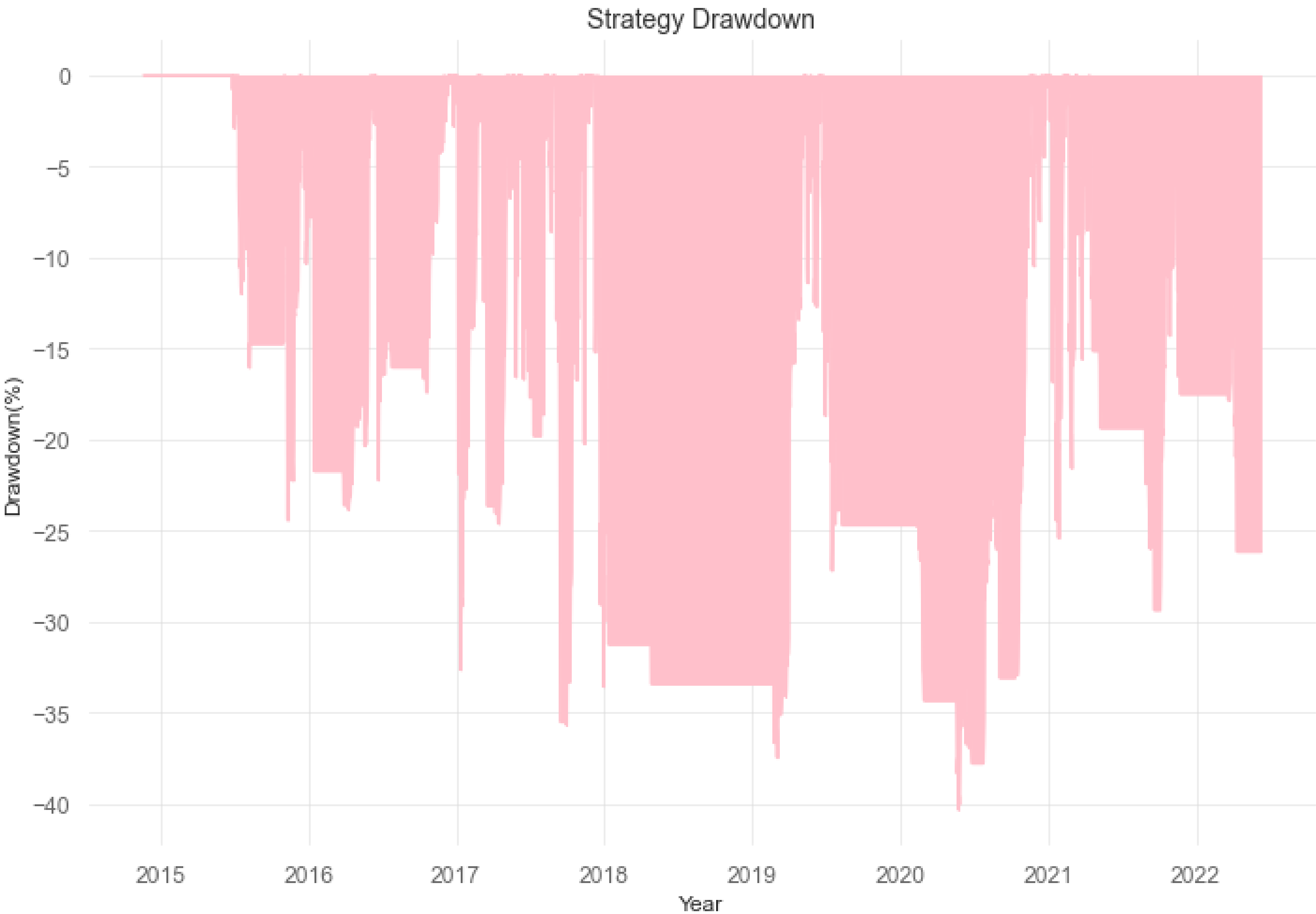
```
# strategy_returns.value_counts()
```

In [25]:

```
# Calculate the running maximum
running_max = np.maximum.accumulate(df["cumulative_returns"].dropna())
# Ensure the value never drops below 1
running_max[running_max < 1] = 1
# Calculate the percentage drawdown
drawdown = ((df["cumulative_returns"])/running_max - 1) * 100

# Calculate the maximum drawdown
```

```
print("Maximum drawdown of the strategy is {0:.2f}%".format(drawdown.min()))

fig = plt.figure(figsize=(10, 7))

# Plot max drawdown
plt.plot(drawdown, color="pink")
# Fill in-between the drawdown
plt.fill_between(drawdown.index, drawdown.values, color="pink")
plt.title("Strategy Drawdown", fontsize=14)
plt.ylabel("Drawdown(%)", fontsize=12)
plt.xlabel("Year", fontsize=12)

plt.tight_layout()
plt.show()
```

```
Maximum drawdown of the strategy is -40.32%
```



In [26]:

```
# Extend pandas functionality with metrics
qs.extend_pandas()
```

In [27]:

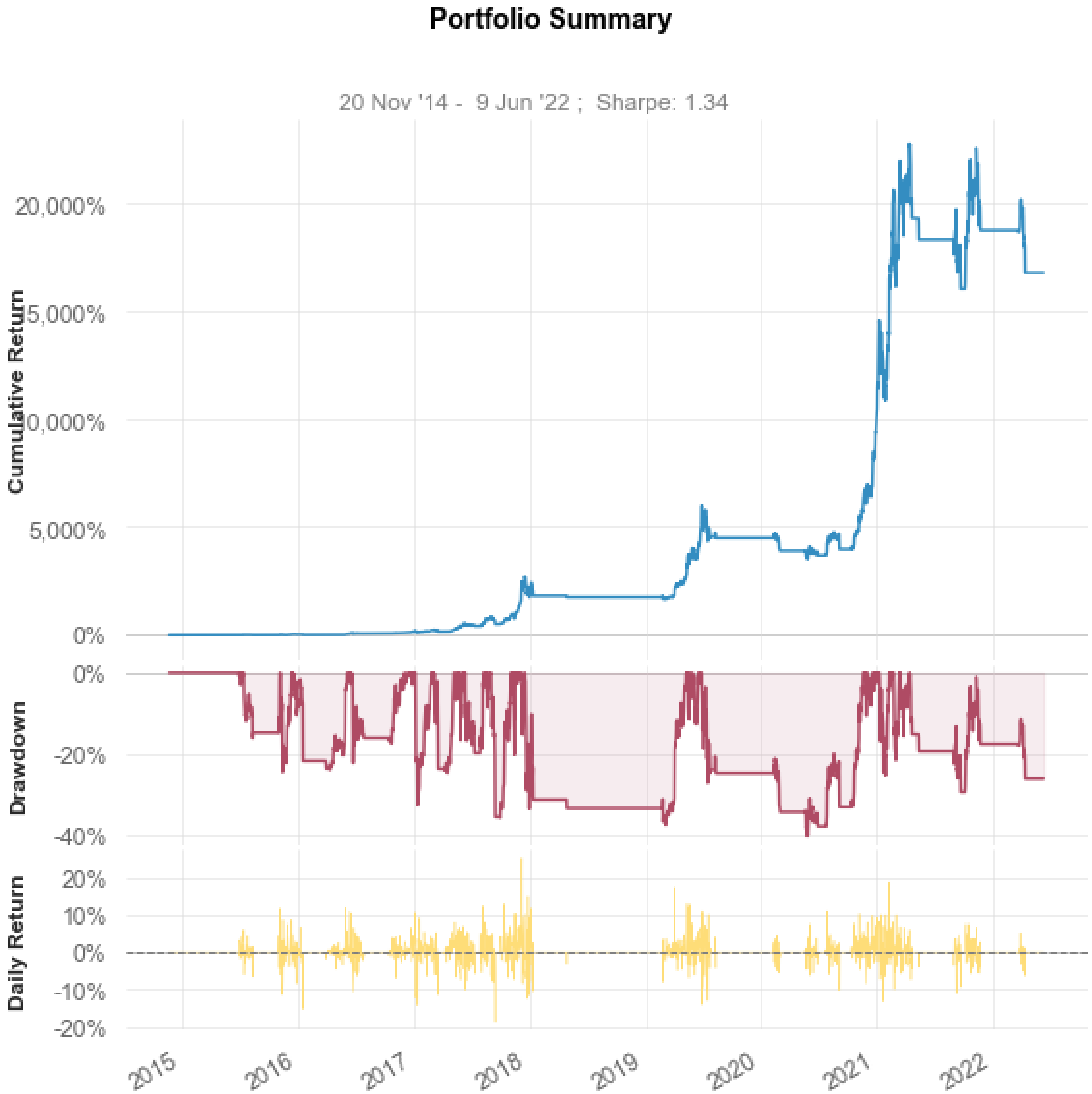
```
# View full perfomance metrics
qs.reports.basic(strategy_returns)
```

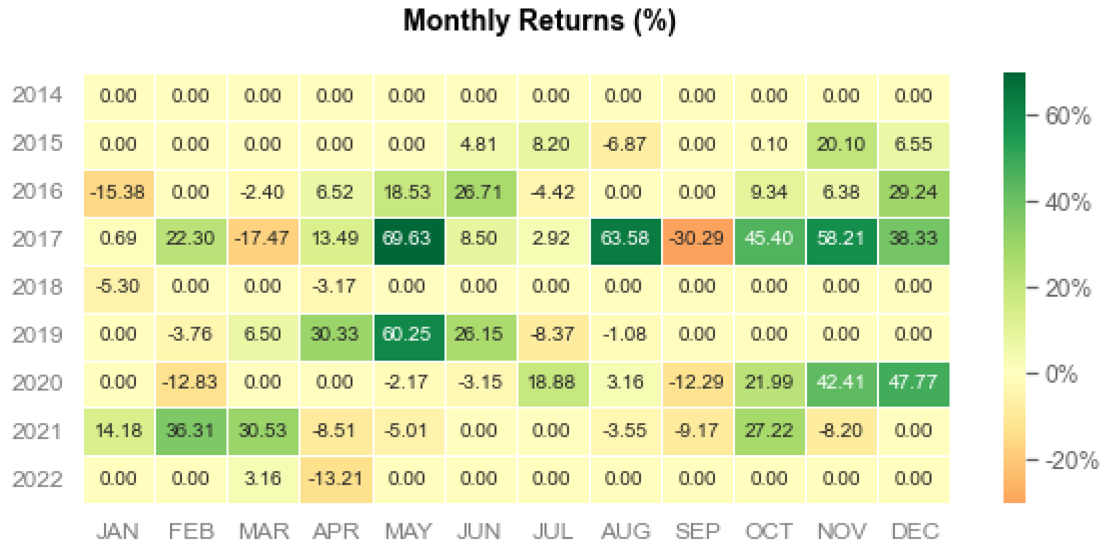
Performance Metrics

```
                    Strategy
------------------  ----------
```

```
Start Period        2014-11-21
End Period          2022-06-09
Risk-Free Rate      0.0%
Time in Market      43.0%

Cumulative Return   16,758.79%
CAGR﹪              97.16%

Sharpe              1.34
Prob. Sharpe Ratio  100.0%
Sortino             2.12
Sortino/√2          1.5
Omega               1.47

Max Drawdown        -40.32%
Longest DD Days     509

Gain/Pain Ratio     0.47
Gain/Pain (1M)      3.59

Payoff Ratio        1.06
Profit Factor       1.47
Common Sense Ratio  1.93
CPC Index           0.9
Tail Ratio          1.31
Outlier Win Ratio   11.87
Outlier Loss Ratio  3.01

MTD                 0.0%
3M                  -10.47%
6M                  -10.47%
YTD                 -10.47%
1Y                  -8.4%
3Y (ann.)           44.73%
5Y (ann.)           99.39%
10Y (ann.)          97.16%
All-time (ann.)     97.16%

Avg. Drawdown       -9.52%
Avg. Drawdown Days  41
Recovery Factor     415.7
Ulcer Index         0.22
Serenity Index      53.19
```

Strategy Visualization





In [28]:
```
# View full perfomance metrics
qs.reports.full(strategy_returns)
```

Performance Metrics

```
                           Strategy
-------------------------  ----------
Start Period               2014-11-21
End Period                 2022-06-09
Risk-Free Rate             0.0%
Time in Market             43.0%

Cumulative Return          16,758.79%
CAGR﹪                     97.16%

Sharpe                     1.34
Prob. Sharpe Ratio         100.0%
Smart Sharpe               1.27
Sortino                    2.12
Smart Sortino              2.0
Sortino/√2                 1.5
Smart Sortino/√2           1.41
Omega                      1.47
```

```
Max Drawdown               -40.32%
Longest DD Days            509
Volatility (ann.)          41.23%
Calmar                     2.41
Skew                       0.65
Kurtosis                   13.54

Expected Daily %           0.19%
Expected Monthly %         5.73%
Expected Yearly %          76.78%
Kelly Criterion            18.52%
Risk of Ruin               0.0%
Daily Value-at-Risk        -4.05%
Expected Shortfall (cVaR)  -4.05%

Max Consecutive Wins       13
Max Consecutive Losses     6
Gain/Pain Ratio            0.47
Gain/Pain (1M)             3.59

Payoff Ratio               1.06
Profit Factor              1.47
Common Sense Ratio         1.93
CPC Index                  0.9
Tail Ratio                 1.31
Outlier Win Ratio          11.87
Outlier Loss Ratio         3.01

MTD                        0.0%
3M                         -10.47%
6M                         -10.47%
YTD                        -10.47%
1Y                         -8.4%
3Y (ann.)                  44.73%
5Y (ann.)                  99.39%
10Y (ann.)                 97.16%
All-time (ann.)            97.16%

Best Day                   25.25%
Worst Day                  -18.74%
Best Month                 69.63%
Worst Month                -30.29%
Best Year                  692.81%
Worst Year                 -10.47%
```

```
Avg. Drawdown              -9.52%
Avg. Drawdown Days         41
Recovery Factor            415.7
Ulcer Index                0.22
Serenity Index             53.19

Avg. Up Month              23.67%
Avg. Down Month            -8.41%
Win Days %                 58.07%
Win Month %                62.5%
Win Quarter %              61.54%
Win Year %                 75.0%
None
```

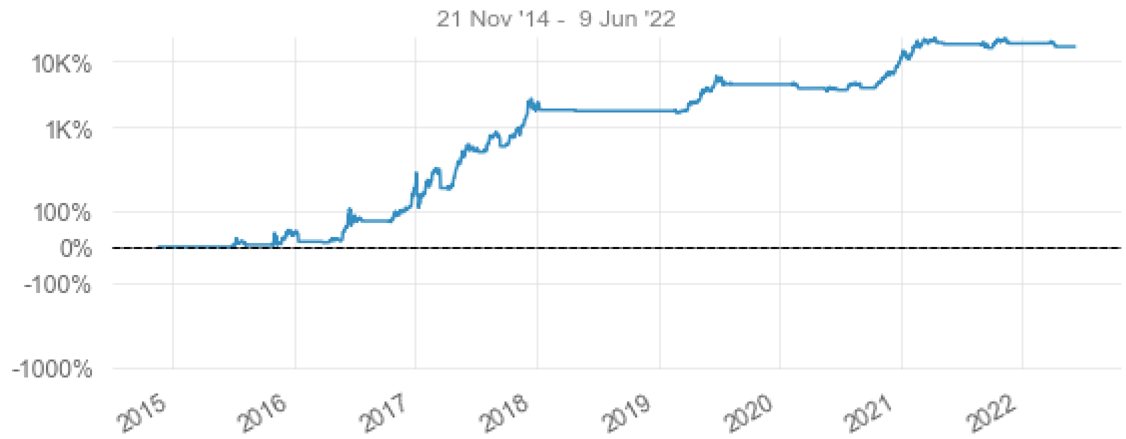
5 Worst Drawdowns

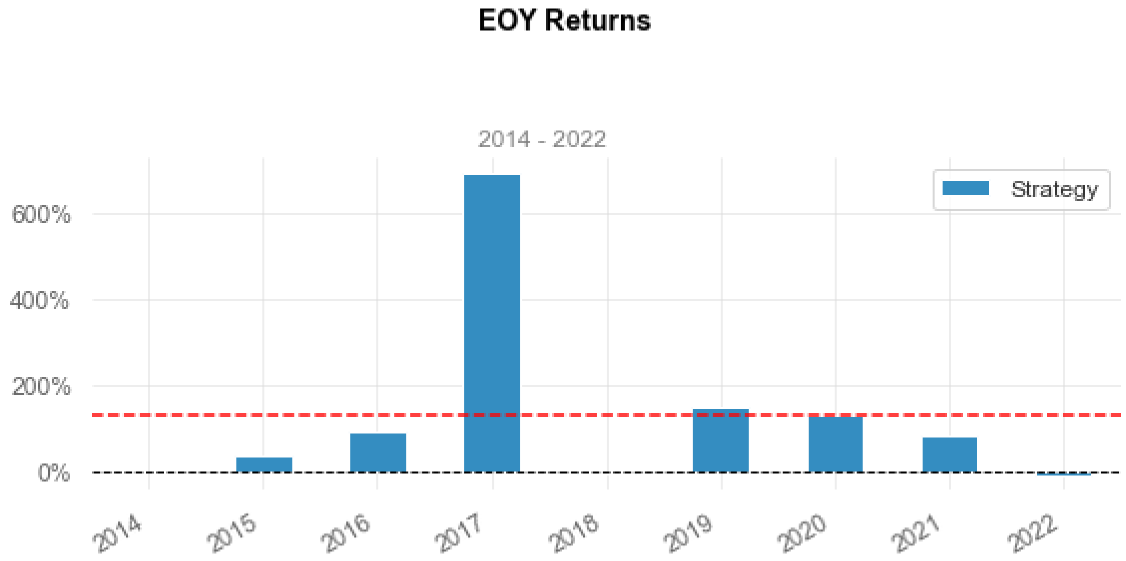
	Start	Valley	End	Days	Max Drawdown	99% Max Drawdown
1	2019-06-27	2020-05-24	2020-11-17	509	-40.315026	-37.710178
2	2017-12-17	2019-03-04	2019-05-09	508	-37.479480	-35.850188
3	2017-09-02	2017-09-29	2017-11-01	60	-35.688230	-35.508102
4	2017-01-05	2017-01-11	2017-02-23	49	-32.645984	-30.301110
5	2021-04-14	2021-09-20	2022-06-09	421	-29.353218	-28.015106

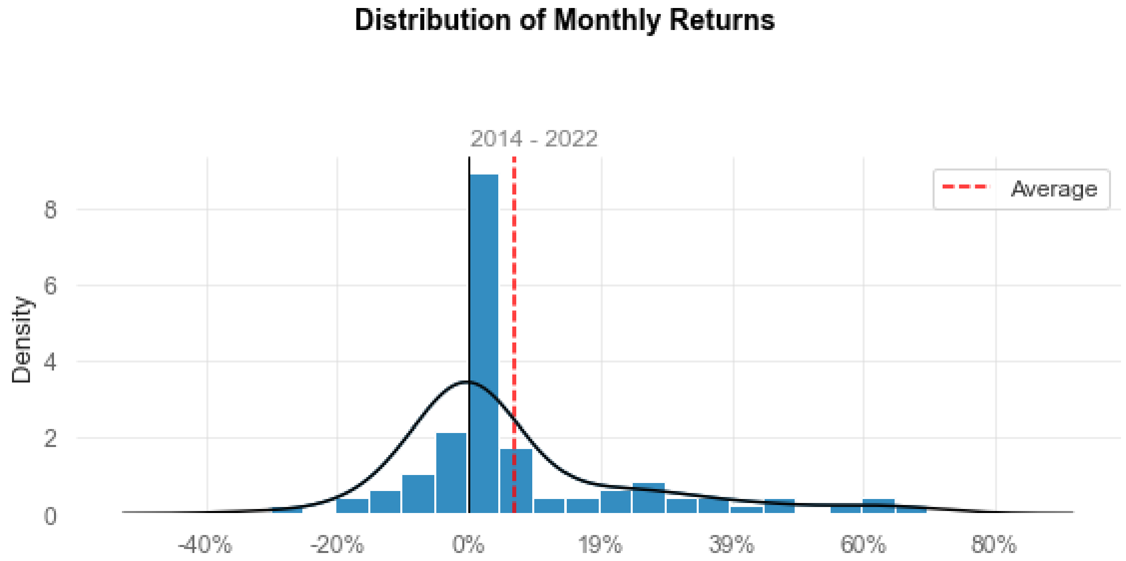
Strategy Visualization

Cumulative Returns

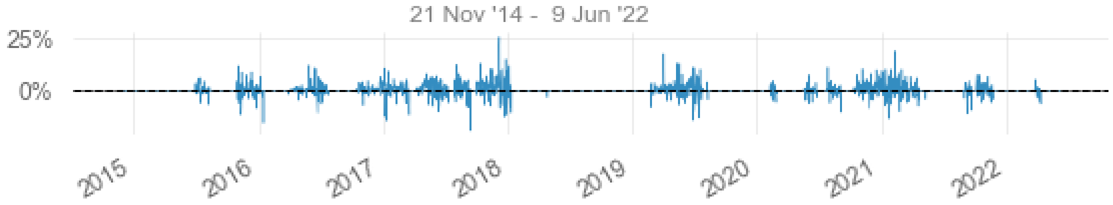
Cumulative Returns (Log Scaled)



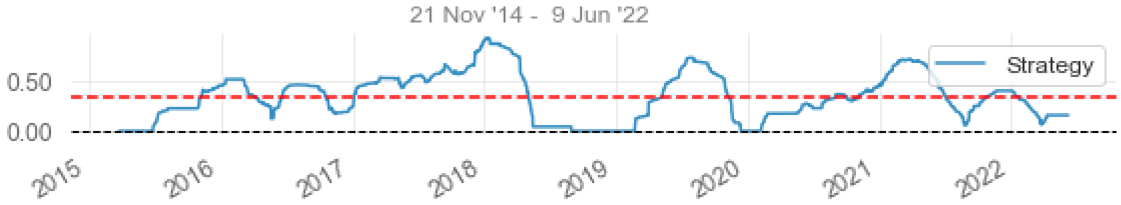

EOY Returns
2014 - 2022
Strategy
600%
400%
200%
0%
2014
2015
2016
2017
2018
2019
2020
2021
2022


Distribution of Monthly Returns
2014 - 2022
Average
Density
8
6
4
2
0
-40%
-20%
0%
19%
39%
60%
80%

Daily Returns



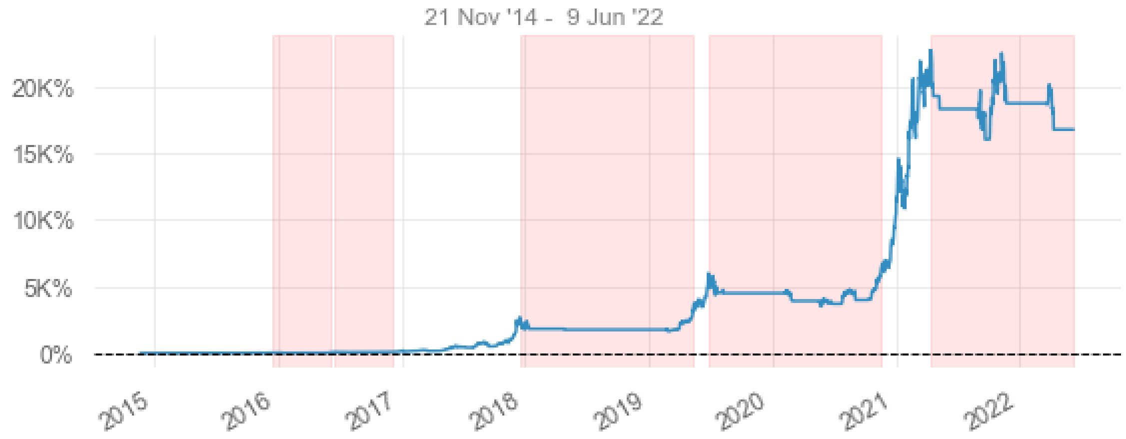
Rolling Volatility (6-Months)



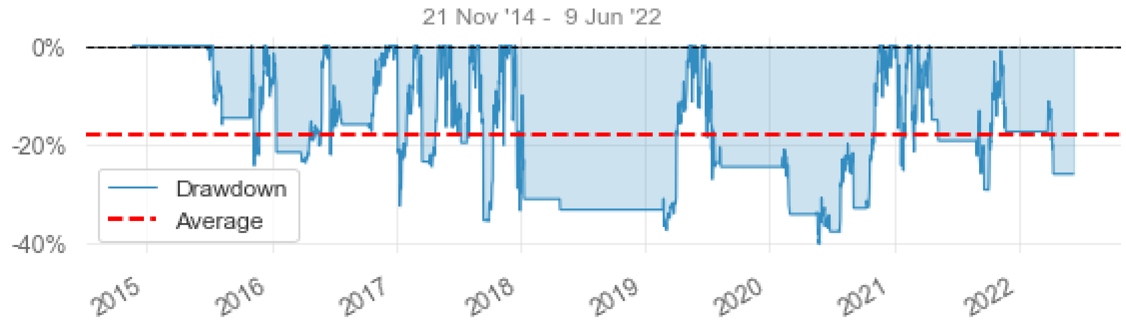
Rolling Sharpe (6-Months)

Rolling Sortino (6-Months)

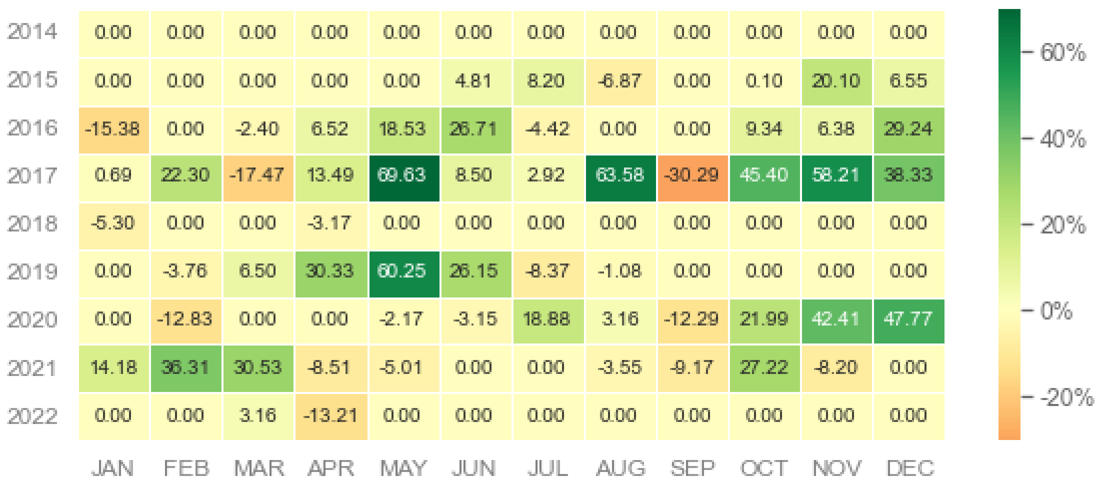
Worst 5 Drawdown Periods



Underwater Plot



Monthly Returns (%)



Return Quantiles