

```
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]:
```

	Open	High	Low	Close	Adj Close	Volume
Date						
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
2022-06-06	29910.283203	31693.291016	29894.187500	31370.671875	31370.671875	31947336829

	Open	High	Low	Close	Adj Close	Volume
Date						
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	30215.279297	30609.310547	30020.265625	30111.998047	30111.998047	21692004719
2022-06-10	30086.400391	30105.738281	29732.906250	29994.623047	29994.623047	23435472896

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]:

	Open	High	Low	Close	Adj Close	Volume	VWAP
Date							
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 coulmsns
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
...
2022-06-06	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	30215.279297	30609.310547	30020.265625	30111.998047	28025.184535
2022-06-10	30086.400391	30105.738281	29732.906250	29994.623047	28026.253558

2824 rows × 5 columns

In [8]:

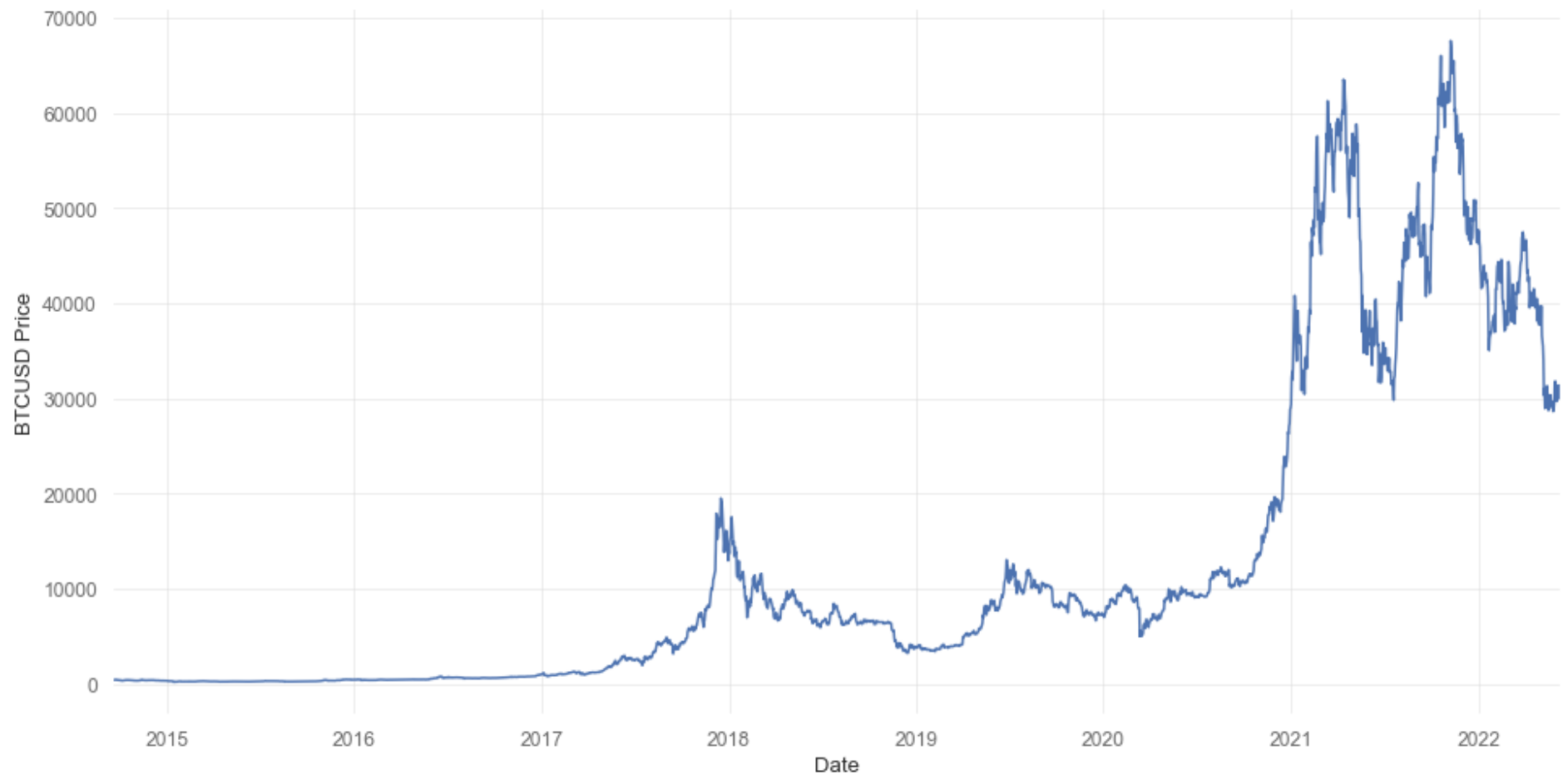
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
DatetimeIndex: 2824 entries, 2014-09-17 to 2022-06-10
Data columns (total 7 columns):
#   Column      Non-Null Count  Dtype
---  -
0   Open        2824 non-null   float64
1   High        2824 non-null   float64
2   Low         2824 non-null   float64
3   Close       2824 non-null   float64
4   Adj Close   2824 non-null   float64
```

```
5   Volume      2824 non-null   int64
6   VWAP         2824 non-null   float64
dtypes: float64(6), int64(1)
memory usage: 176.5 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()
```

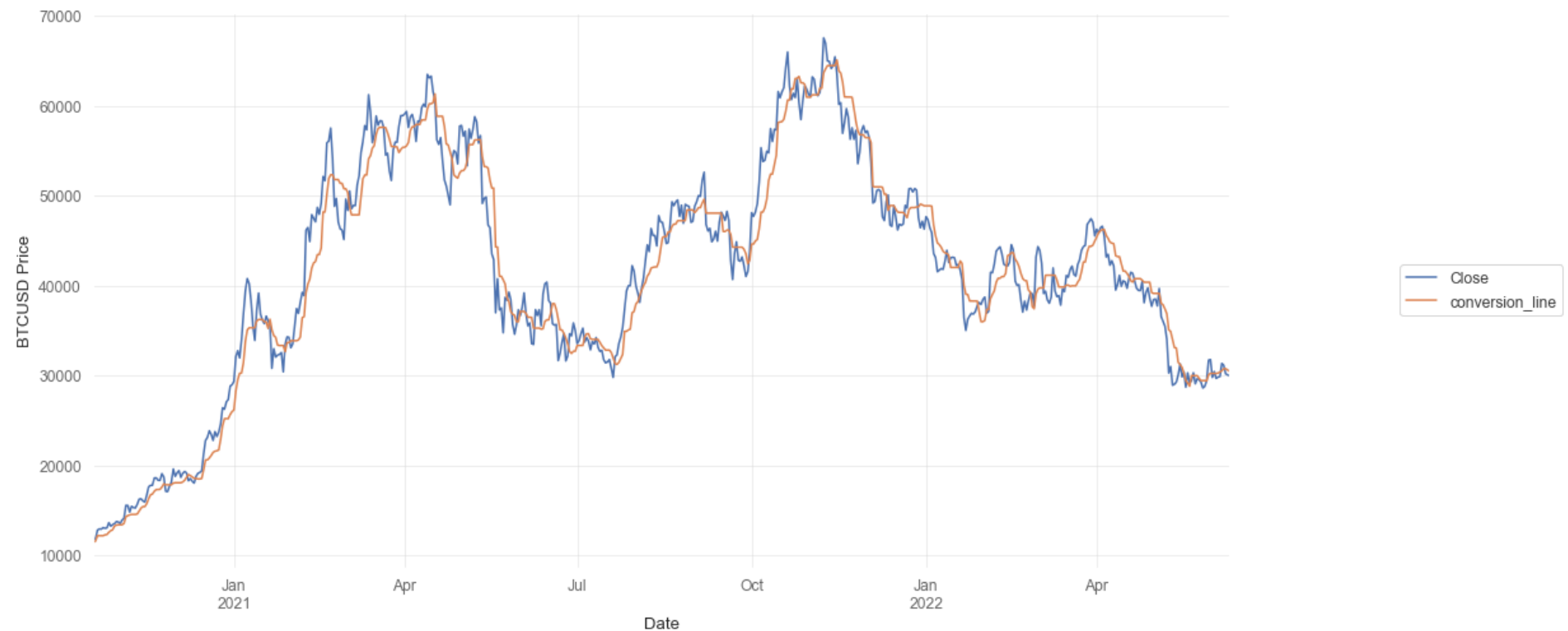


In [11]:

```

# 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)
```

```
# 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]:

```
# 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]:

	Open	High	Low	Close	Adj Close	Volume	VWAP	conversion_line	base_line	leading_span_A	leading_span_B	
Date												
2015-08-03	282.806000	285.471008	280.233002	281.226990	281.226990	21474100	286.633870	287.651489	290.740005	251.304001	244.581505	51.7
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

	Open	High	Low	Close	Adj Close	Volume	VWAP	conversion_line	base_line	leading_span_A	leading_span_B	
Date												
2015-08-11	264.342010	270.385986	264.093994	270.385986	270.385986	25433900	286.223646	273.091492	279.120987	280.838257	267.845009	44.4
2015-08-12	270.597992	270.673004	265.468994	266.376007	266.376007	26815400	286.160909	273.091492	279.120987	281.963505	267.845009	41.1
2015-08-13	266.183014	266.231995	262.841003	264.079987	264.079987	27685500	286.089082	272.984497	279.120987	283.384754	267.845009	39.8
2015-08-14	264.131989	267.466003	261.477997	265.679993	265.679993	27091200	286.024324	271.186996	279.120987	283.384754	267.845009	41.0
2015-08-15	265.528992	266.666992	261.295990	261.550995	261.550995	19321100	285.969068	270.429993	279.120987	283.384754	267.845009	38.1
2015-08-16	261.865997	262.440002	257.040985	258.506989	258.506989	29717000	285.874031	268.484497	277.407486	284.059757	267.845009	36.4
2015-08-17	258.489990	260.505005	257.117004	257.976013	257.976013	21617900	285.803975	263.856995	277.407486	284.488758	267.845009	36.0
2015-08-18	257.925995	257.993011	211.078995	211.078995	211.078995	42147200	285.439916	240.875999	254.426491	285.299007	267.845009	18.1
2015-08-19	225.671005	237.408997	222.766006	226.684006	226.684006	60869200	285.029388	240.875999	254.426491	285.299007	267.845009	30.1
2015-08-20	226.899002	237.365005	226.899002	235.350006	235.350006	32275000	284.846017	240.875999	254.426491	284.734501	267.845009	36.1
2015-08-21	235.354996	236.432007	231.723999	232.569000	232.569000	23173800	284.707837	239.272499	254.426491	281.425255	267.845009	35.1
2015-08-22	232.662003	234.957001	222.703995	230.389999	230.389999	23205900	284.564443	239.272499	253.863991	281.779751	268.406509	34.4
2015-08-23	230.376007	232.705002	225.580002	228.169006	228.169006	18406600	284.446602	238.872993	252.807503	281.550255	268.523003	33.0
2015-08-24	228.112000	228.139008	210.442993	210.494995	210.494995	59220700	283.952755	236.441498	250.284500	282.668755	268.523003	27.1

	Open	High	Low	Close	Adj Close	Volume	VWAP	conversion_line	base_line	leading_span_A	leading_span_B	
Date												
2015-08-25	210.067993	226.320999	199.567001	221.608994	221.608994	61089200	283.526227	230.036003	244.263008	283.366005	268.523003	35.0
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	37.0
2015-08-28	224.701004	235.218994	220.925995	231.395996	231.395996	31336600	282.998631	218.466003	242.640999	285.187252	268.616508	41.0
2015-08-29	231.548996	233.222000	227.330002	229.779999	229.779999	17142500	282.897616	217.999504	242.640999	286.312500	271.161507	41.0
2015-08-30	229.895004	232.067993	226.246994	228.761002	228.761002	19412600	282.781501	217.392998	242.534004	287.951996	271.202003	40.0
2015-08-31	229.113998	231.955994	225.914993	230.056000	230.056000	20710700	282.661125	217.392998	240.736504	287.951996	271.580505	41.0
2015-09-01	230.255997	231.216003	226.860001	228.121002	228.121002	20575200	282.537701	217.392998	239.979500	288.520744	271.802010	40.0
2015-09-02	228.026993	230.576996	226.475006	229.283997	229.283997	18760400	282.428045	217.392998	239.747505	289.195747	271.802010	41.0
2015-09-03	229.324005	229.604996	226.667007	227.182999	227.182999	17482000	282.322242	227.711494	235.120003	289.624748	273.199005	40.0
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	50.0
2015-09-07	239.934006	242.106003	238.722000	239.847000	239.847000	21192200	281.882741	234.413498	233.516502	277.038246	277.379509	50.0

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

In [19]:

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

Out[19]:

```
0.0    2709
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]:

```

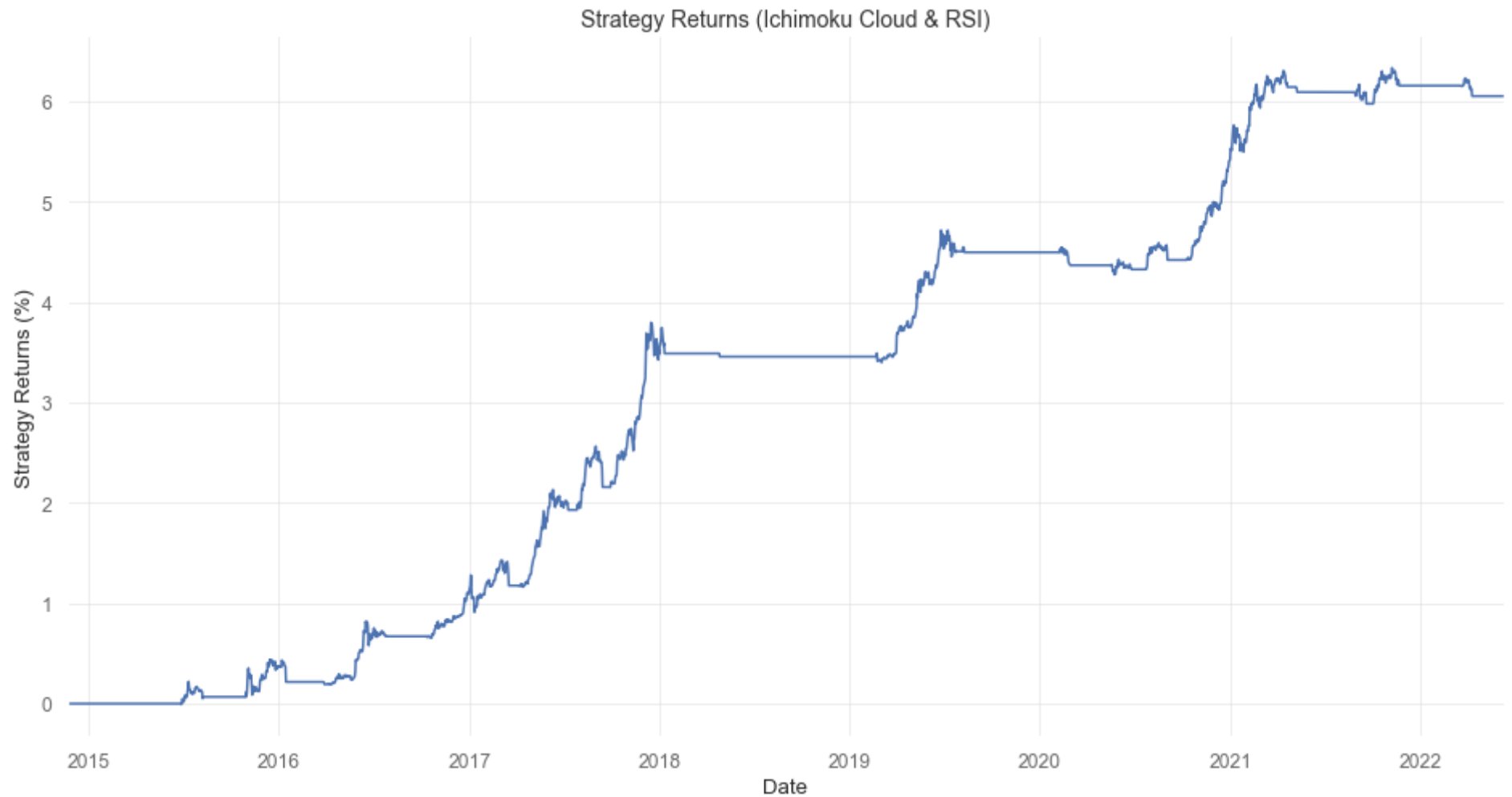
# Calculate daily returns
daily_returns = df.Close.pct_change()

# 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
```

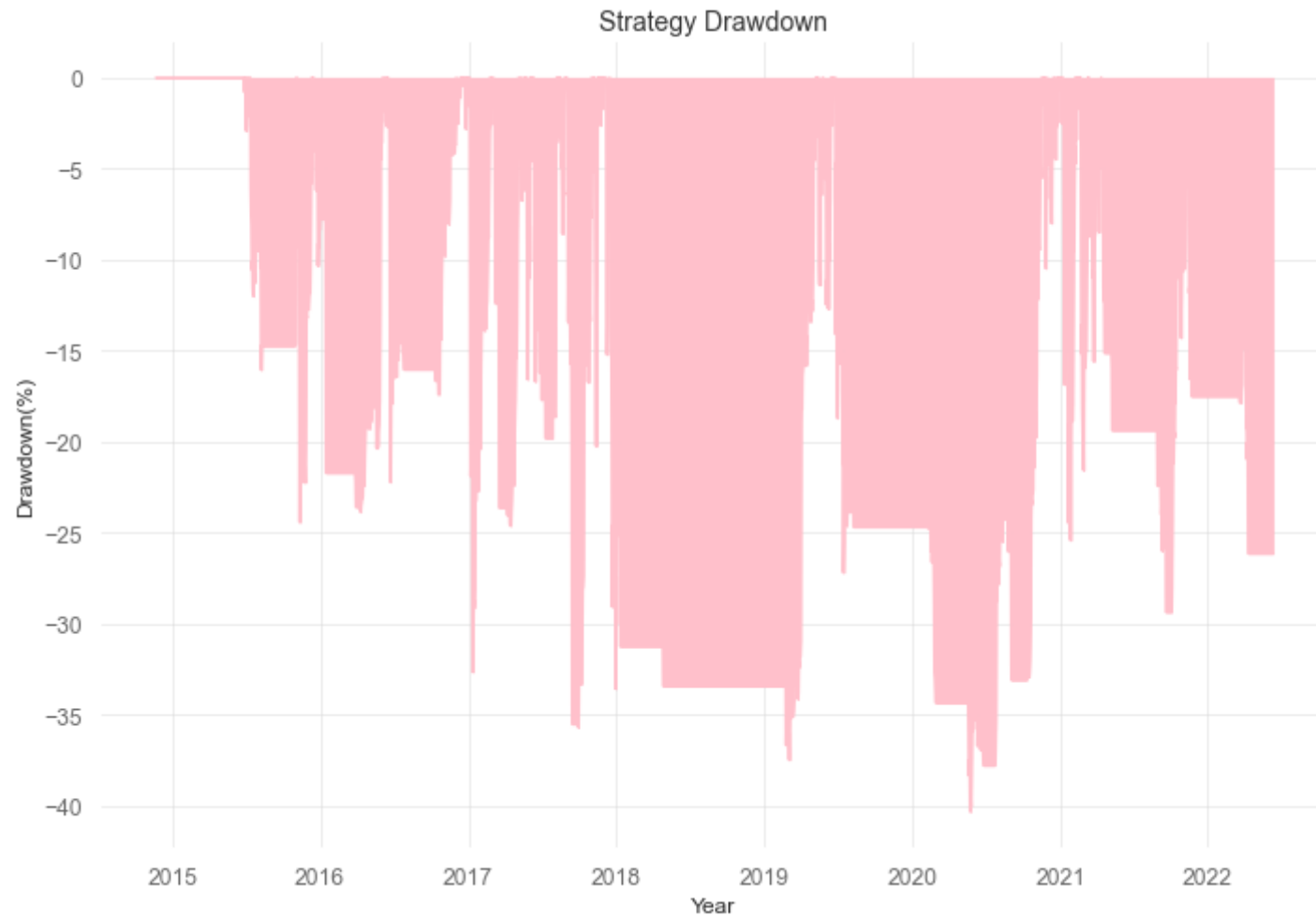
```
print("Maximum drawdown of the strategy is {:.2f}%".format(drawdown.min()))

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 [27]: # Extend pandas functionality with metrics  
qs.extend_pandas()
```

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

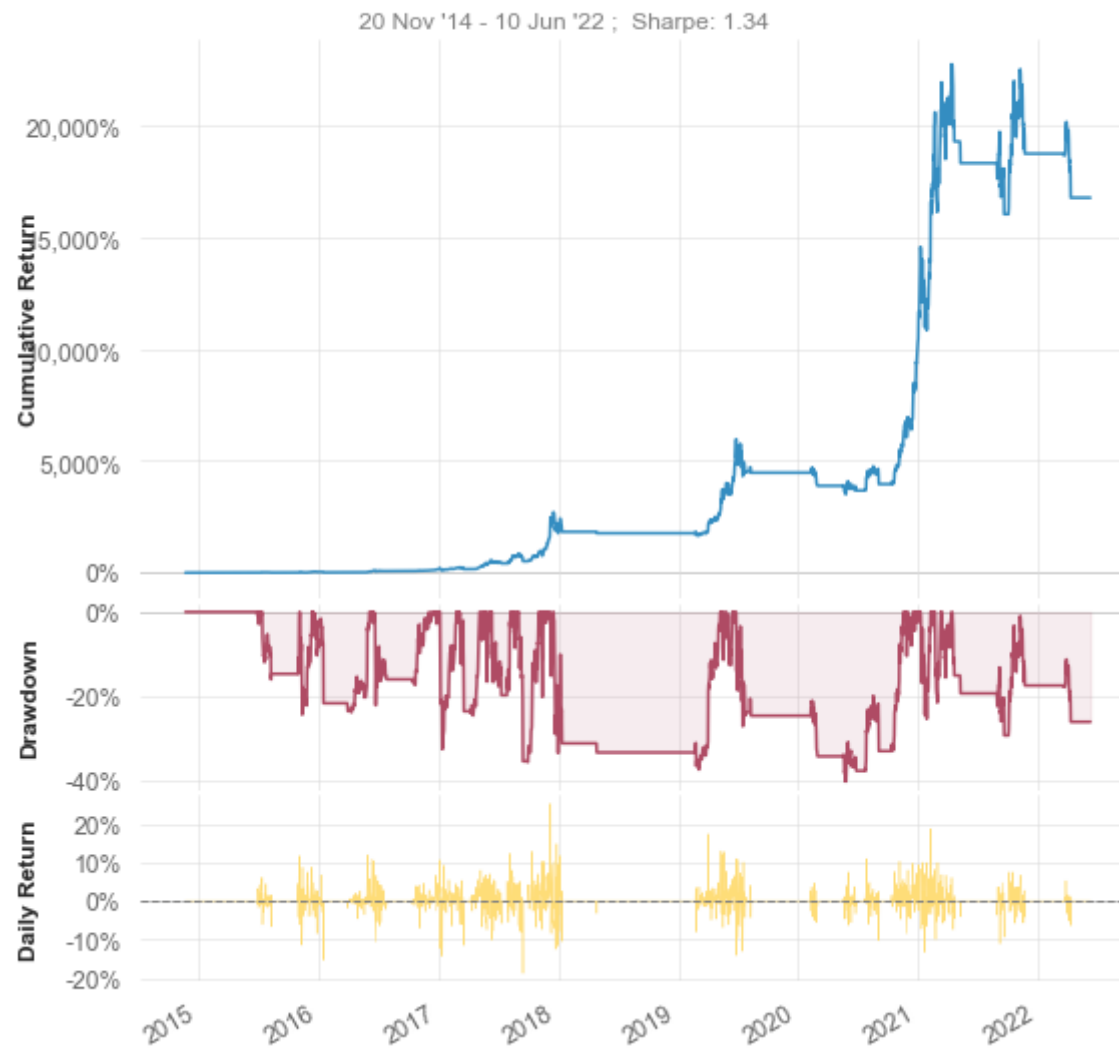
Performance Metrics

Strategy

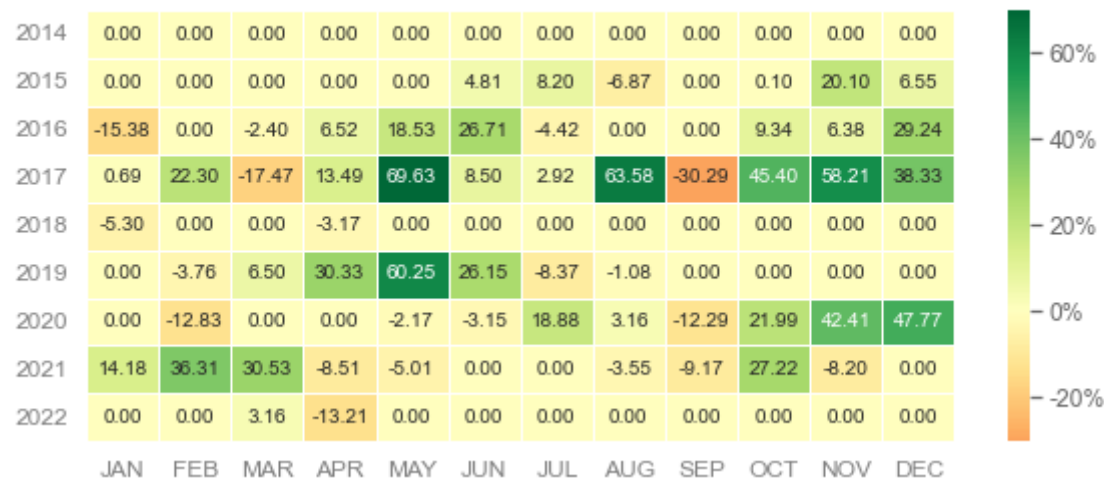
Start Period	2014-11-21
End Period	2022-06-10
Risk-Free Rate	0.0%
Time in Market	43.0%
Cumulative Return	16,758.79%
CAGR %	97.11%
Sharpe	1.34
Prob. Sharpe Ratio	100.0%
Sortino	2.12
Sortino/√2	1.5
Omega	1.47
Max Drawdown	-40.32%
Longest DD Days	509
Gain/Pain Ratio	0.47
Gain/Pain (1M)	3.59
Payoff Ratio	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.)	43.59%
5Y (ann.)	100.23%
10Y (ann.)	97.11%
All-time (ann.)	97.11%
Avg. Drawdown	-9.52%
Avg. Drawdown Days	41
Recovery Factor	415.7
Ulcer Index	0.22
Serenity Index	53.18

Strategy Visualization

Portfolio Summary



Monthly Returns (%)



In [29]:

```
# View full performance metrics
qs.reports.full(strategy_returns, "BTC-USD")
```

Performance Metrics

	Strategy	Benchmark
-----	-----	-----
Start Period	2014-11-21	2014-11-21
End Period	2022-06-10	2022-06-10
Risk-Free Rate	0.0%	0.0%
Time in Market	43.0%	100.0%
Cumulative Return	16,758.79%	8,449.18%
CAGR %	97.11%	80.17%
Sharpe	1.34	0.97
Prob. Sharpe Ratio	100.0%	99.94%
Smart Sharpe	1.27	0.92
Sortino	2.12	1.43
Smart Sortino	2.0	1.35
Sortino/√2	1.5	1.01
Smart Sortino/√2	1.41	0.95
Omega	1.47	1.47

Max Drawdown	-40.32%	-83.4%
Longest DD Days	509	1079
Volatility (ann.)	41.22%	61.44%
R^2	0.45	0.45
Information Ratio	-0.01	-0.01
Calmar	2.41	0.96
Skew	0.65	-0.16
Kurtosis	13.55	7.3
Expected Daily %	0.19%	0.16%
Expected Monthly %	5.73%	4.95%
Expected Yearly %	76.78%	63.93%
Kelly Criterion	18.52%	10.98%
Risk of Ruin	0.0%	0.0%
Daily Value-at-Risk	-4.05%	-6.13%
Expected Shortfall (cVaR)	-4.05%	-6.13%
Max Consecutive Wins	13	13
Max Consecutive Losses	6	7
Gain/Pain Ratio	0.47	0.2
Gain/Pain (1M)	3.59	1.37
Payoff Ratio	1.06	1.06
Profit Factor	1.47	1.2
Common Sense Ratio	1.93	1.28
CPC Index	0.9	0.69
Tail Ratio	1.31	1.06
Outlier Win Ratio	12.71	4.14
Outlier Loss Ratio	3.55	3.65
MTD	0.0%	-5.65%
3M	-10.47%	-28.56%
6M	-10.47%	-37.08%
YTD	-10.47%	-35.23%
1Y	-8.4%	-19.68%
3Y (ann.)	43.59%	34.67%
5Y (ann.)	100.23%	65.45%
10Y (ann.)	97.11%	80.17%
All-time (ann.)	97.11%	80.17%
Best Day	25.25%	25.25%
Worst Day	-18.74%	-37.17%
Best Month	69.63%	69.63%
Worst Month	-30.29%	-36.41%

Best Year	692.81%	1368.9%
Worst Year	-10.47%	-73.56%
Avg. Drawdown	-9.52%	-11.41%
Avg. Drawdown Days	41	43
Recovery Factor	415.7	101.31
Ulcer Index	0.22	0.42
Serenity Index	53.18	10.68
Avg. Up Month	23.67%	26.84%
Avg. Down Month	-9.64%	-11.14%
Win Days %	58.07%	54.19%
Win Month %	62.5%	55.43%
Win Quarter %	61.54%	54.84%
Win Year %	75.0%	66.67%
Beta	0.45	-
Alpha	0.28	-
Correlation	67.06%	-
Treynor Ratio	37239.85%	-
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	2022-06-10	422	-29.353218	-28.015106

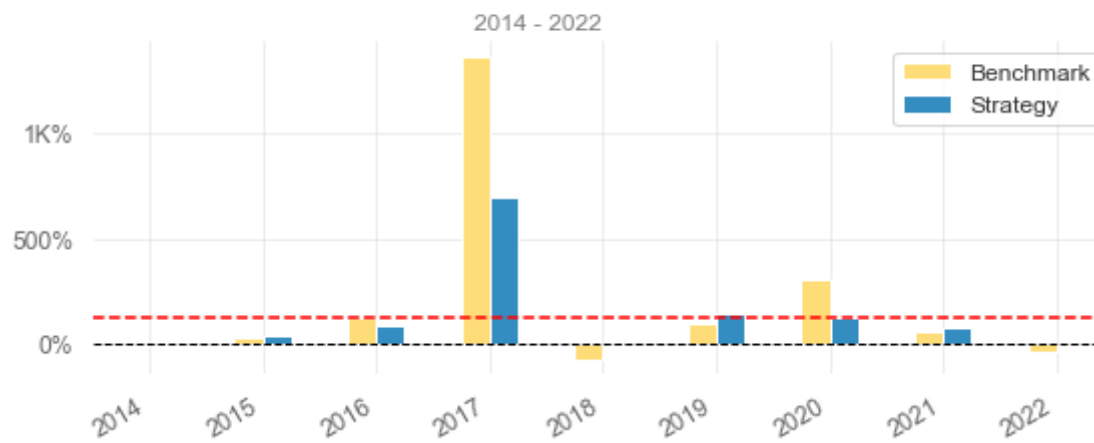
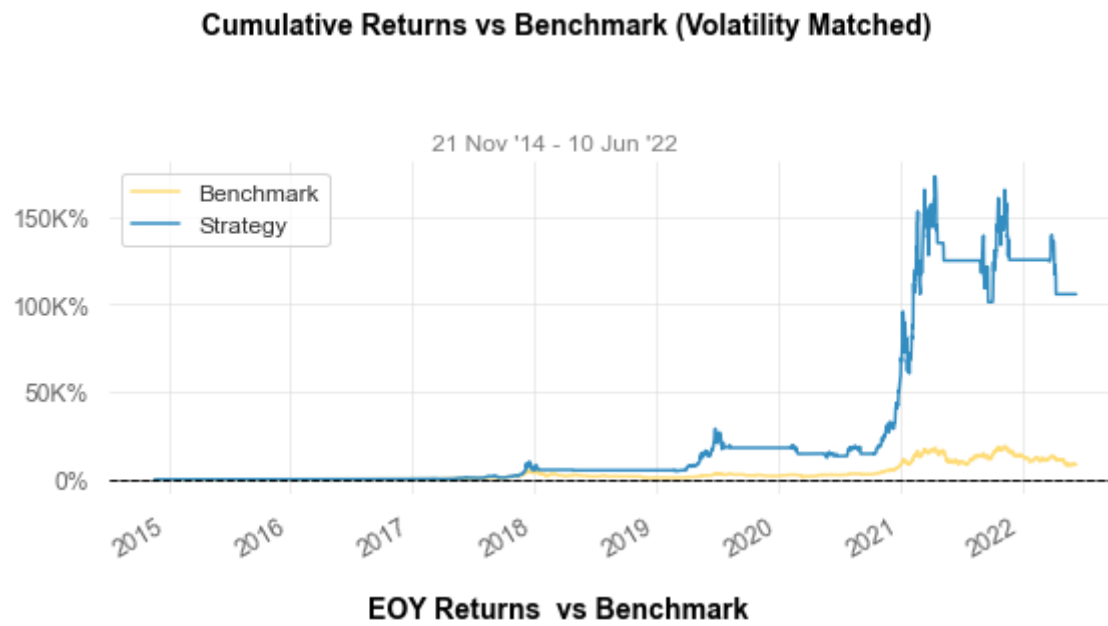
Strategy Visualization

Cumulative Returns vs Benchmark

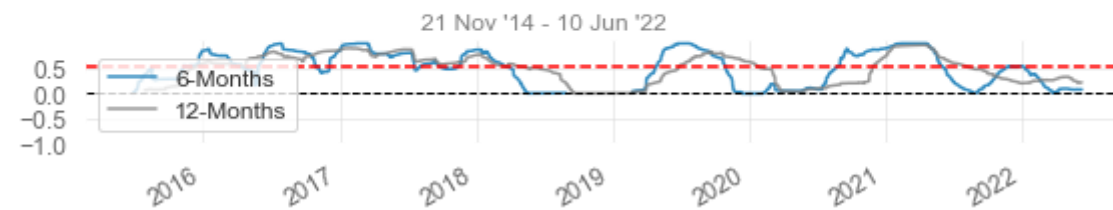
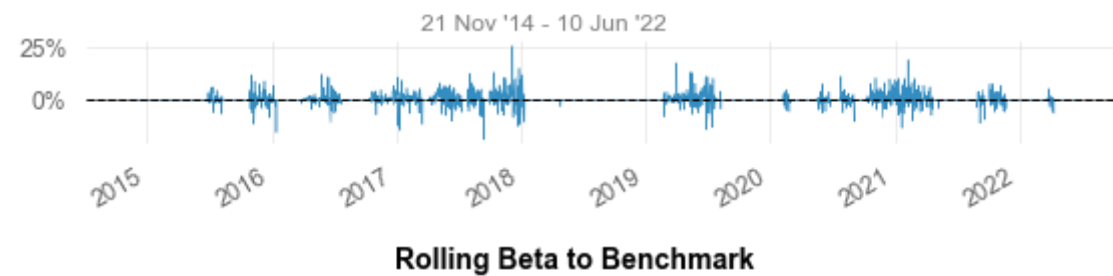
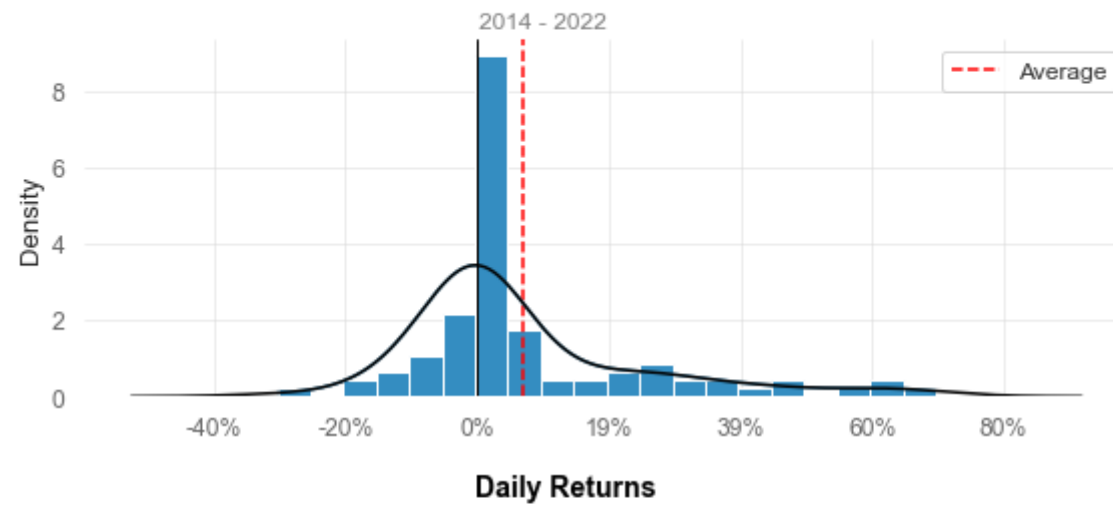


Cumulative Returns vs Benchmark (Log Scaled)

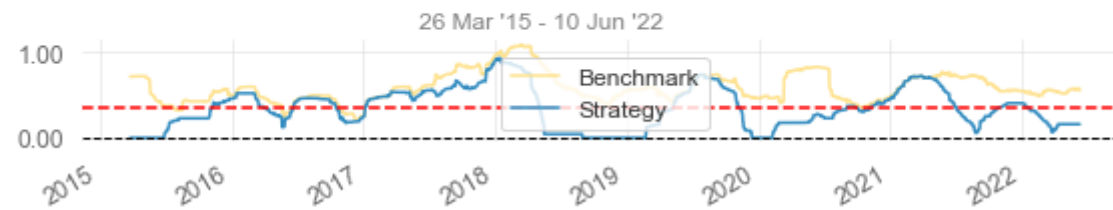




Distribution of Monthly Returns



Rolling Volatility (6-Months)



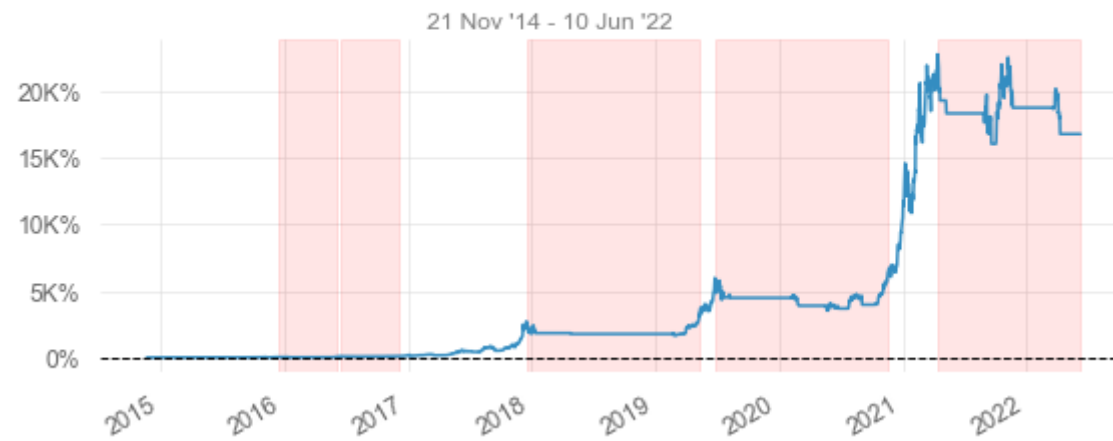
Rolling Sharpe (6-Months)



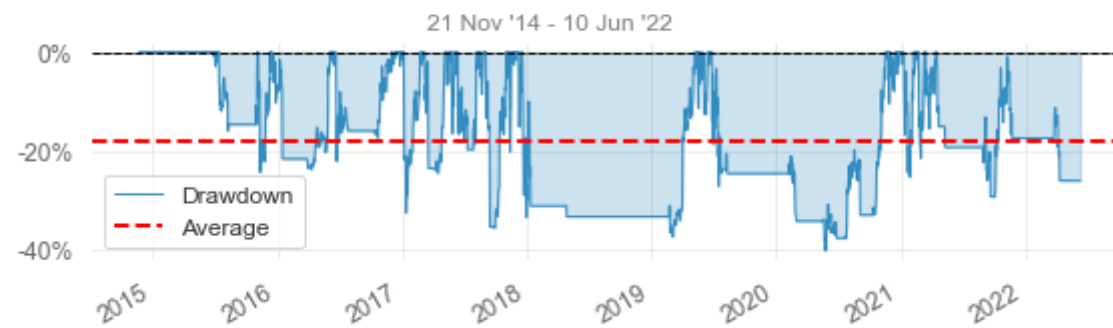
Rolling Sortino (6-Months)



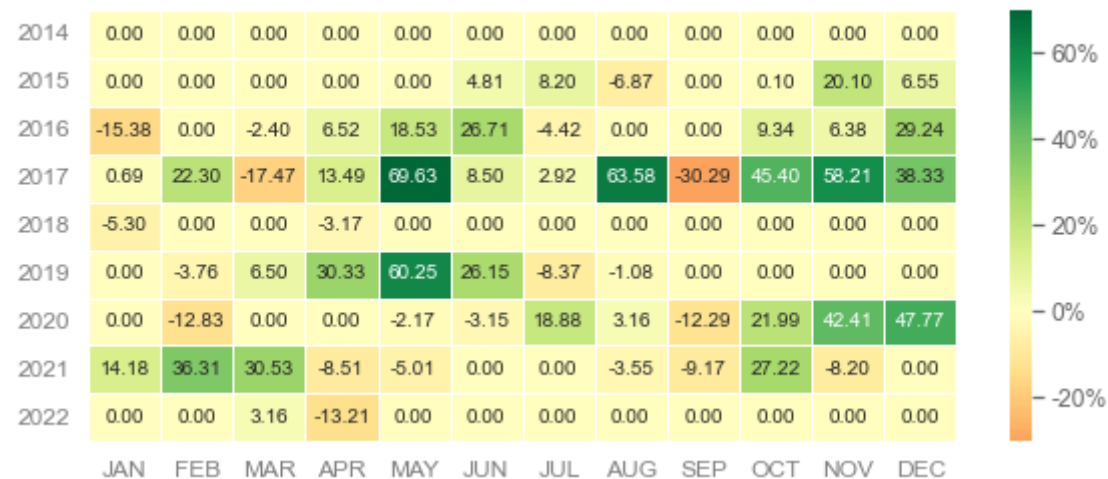
Worst 5 Drawdown Periods



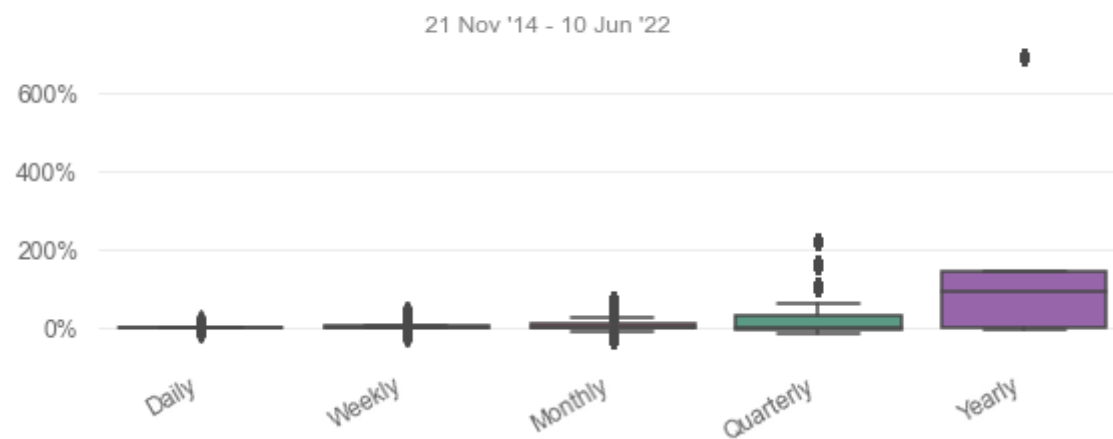
Underwater Plot



Monthly Returns (%)



Return Quantiles



In []: