

```
[118]: import warnings
warnings.filterwarnings('ignore')

import pandas as pd
from pandas_datareader import data as pdr
import numpy as np
from datetime import datetime, date, timedelta

import yfinance as yfin
from var import VaR
import scipy.stats

import matplotlib.pyplot as plt
import seaborn as sns
#from yahoo_financials import YahooFinancials

#pd.set_option('display.float_format', '{:.10f}'.format)
pd.set_option('display.float_format', lambda x: f'{x:.4f}')


[119]: start_date = datetime(2022, 1, 1)
end_date = datetime.now()
alpha = 0.05

yfin.pdr_override()

#start_date = "2022-01-01"
#end_date = "2023-08-31"
#alpha = 0.01
```

## Assignment

Create a Github account if you do not already have one and download a VAR library. Using the library that you have chosen and historical data (available from Yahoo Finance and other sources) calculate the VaR for your investment portfolio. Document your work in a presentation and post it to the Discussion Forum and comment on and discuss the document and posted work of others.

## Variables

```
[119]: start_date = datetime(2022, 1, 1)
end_date = datetime.now()
alpha = 0.05

yfin.pdr_override()

#start_date = "2022-01-01"
#end_date = "2023-08-31"
#alpha = 0.01
```

## Functions

### Load Data

```
[120]: folio_df = pd.read_csv('https://raw.githubusercontent.com/dsimband/DATA618/main/w5/data/DATA618_Portfolio.csv',
                           dtype={
                               'ID': 'int',
                               'Price': 'float',
                               'Shares': 'float',
                               'Value': 'float',
                           })

folio_df = folio_df[folio_df['Shares'] > 0]
folio_df = folio_df.groupby(['Ticker', 'BondName', 'Class'])[['Shares', 'Value']].sum()
folio_df.reset_index(inplace=True)
#folio_df['Morningstar_Category'].fillna('Other', inplace=True)
folio_df
```

	Ticker	BondName	Class	Shares	Value
0	ALTVX	AB Municipal Income National Advisor	Interest Rate Sensitive	106,383.0000	1,000.0000
1	BLUEX	AMG Veritas Global Real Return I	Economically Sensitive	14,201.0000	500.0000
2	BPLSX	Boston Partners Long/Short Equity Instl	Economically Sensitive	49,967.0000	750.0000
3	C_A_S_H	Cash	Cash	4,469,000.0000	4,469.0000
4	DFAR	Dimensional US Real Estate ETF	Economically Sensitive	108,468.0000	2,250.0000
...	...	...	...	...	...
30	VIGI	Vanguard Intl Div Apprec ETF	Economically Sensitive	40,481.0000	3,000.0000
31	VNQ	Vanguard Real Estate ETF	Economically Sensitive	40,221.0000	3,250.0000
32	VO	Vanguard Mid-Cap ETF	Economically Sensitive	9,234.0000	2,000.0000
33	VONG	Vanguard Russell 1000 Growth ETF	Economically Sensitive	41,501.0000	3,000.0000
34	VTEB	Vanguard Tax-Exempt Bond ETF	Interest Rate Sensitive	20,333.0000	1,000.0000

35 rows × 5 columns

```
[121]: folio_df.groupby(['Class'])[['Value']].sum()
```

```
[121]:      Value
```

Class	Value
Cash	4,469.0000
Economically Sensitive	50,250.0000
Interest Rate Sensitive	29,000.0000

### Calculate Percentage

```
[122]: portfolio_total = folio_df['Value'].sum()
folio_df['port_percent'] = folio_df['Value'] / portfolio_total

[123]: ticker_lst = list(folio_df['Ticker'])
weights = (folio_df['port_percent']).values

[124]: price_df = pdr.get_data_yahoo(ticker_lst, start=start_date, end=end_date)
price_df = price_df[['Adj Close']]
price_df.columns = price_df.columns.get_level_values(1)
price_df['C_A_S_H'] = 1

price_df
[******100%*****] 35 of 35 completed

1 Failed download:
  FCA.C.U11: Execution failed: No timetags found. symbol may be deleted!
```

[124]:	ALTVX	BLUEX	BPLSX	C_A_S_H	DFAR	FREL	FSMD	VGCAX	VICSX	VIGI	VNQ	VO	VONG	VTEB
	Date													
2022-01-03	10.4183	36.7510	13.1206		1	NaN	32.6081	35.1562	...	20.7575	23.9542	82.4521	107.5871	246.6520
2022-01-04	10.4087	36.6256	13.3690		1	NaN	32.6081	35.4690	...	20.7382	23.9542	82.2496	107.4563	246.4671
2022-01-05	10.3990	36.3122	13.4133		1	NaN	31.6710	34.6969	...	20.6996	23.8771	81.1115	104.3810	240.2957
2022-01-06	10.3796	36.2943	13.4932		1	NaN	31.6900	34.9129	...	20.6610	23.8097	80.5425	104.4745	240.9089
2022-01-07	10.3700	36.3480	13.5109		1	NaN	31.4912	34.6871	...	20.6225	23.7519	80.6389	103.7828	239.4682
...	...	...	...		...	...	...	...	...	...	...	...	...	...
2023-09-25	9.2300	34.2600	15.0000		1	19.7800	23.0400	32.2600	...	18.2200	20.6100	72.2400	76.6245	209.5800
2023-09-26	9.2200	33.8200	14.8800		1	19.4100	22.6100	31.8900	...	18.2000	20.5800	71.4600	75.2281	206.6000
2023-09-27	9.2000	33.8100	14.8600		1	19.2600	22.4400	32.1000	...	18.1400	20.4800	71.3000	74.7230	207.2900
2023-09-28	9.1500	34.1200	14.9300		1	19.4800	22.6900	32.4350	...	18.1400	20.5100	71.6100	75.4400	208.8600
2023-09-29	9.1700	33.9900	14.8200		1	19.5200	22.7500	32.2700	...	17.9500	20.4400	71.3300	75.6600	208.2400
438 rows × 35 columns														

```
[125]: percent_df = price_df.pct_change()
percent_df = percent_df[1:]
percent_df.fillna(0, inplace=True)
percent_df.index = pd.to_datetime(percent_df.index)

percent_df
```

[125]:	ALTVX	BLUEX	BPLSX	C_A_S_H	DFAR	FREL	FSMD	VGCAX	VICSX	VIGI	VNQ	VO	VONG	VTEB
	Date													
2022-01-04	-0.0009	-0.0034	0.0189	0.0000	0.0000	0.0000	0.0089	...	-0.0009	0.0000	-0.0025	-0.0012	-0.0007	-0.0107
2022-01-05	-0.0009	-0.0086	0.0033	0.0000	0.0000	-0.0287	-0.0218	...	-0.0019	-0.0032	-0.0138	-0.0286	-0.0250	-0.0319
2022-01-06	-0.0019	-0.0005	0.0060	0.0000	0.0000	0.0006	0.0062	...	-0.0019	-0.0028	-0.0070	0.0009	0.0026	-0.0021
2022-01-07	-0.0009	0.0015	0.0013	0.0000	0.0000	-0.0063	-0.0065	...	-0.0019	-0.0024	0.0012	-0.0066	-0.0060	-0.0110
2022-01-10	-0.0028	0.0047	0.0007	0.0000	0.0000	-0.0066	-0.0028	...	-0.0009	-0.0016	-0.0087	-0.0058	-0.0033	-0.0008
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...
2023-09-25	-0.0065	-0.0003	0.0040	0.0000	-0.0010	-0.0009	0.0031	...	-0.0049	-0.0053	-0.0017	-0.0009	0.0027	0.0052
2023-09-26	-0.0011	-0.0128	-0.0080	0.0000	-0.0187	-0.0187	-0.0115	...	-0.0011	-0.0015	-0.0108	-0.0182	-0.0142	-0.0164
2023-09-27	-0.0022	-0.0003	-0.0013	0.0000	-0.0077	-0.0075	0.0066	...	-0.0033	-0.0049	-0.0022	-0.0067	0.0033	0.0015
2023-09-28	-0.0054	0.0092	0.0047	0.0000	0.0114	0.0111	0.0104	...	0.0000	0.0015	0.0043	0.0096	0.0076	0.0077
2023-09-29	0.0022	-0.0038	-0.0074	0.0000	0.0021	0.0026	-0.0051	...	-0.0105	-0.0034	-0.0039	0.0029	-0.0030	-0.0006
437 rows × 35 columns														

```
[126]: price_df.query("index == '2023-09-11 00:00:00'")
```

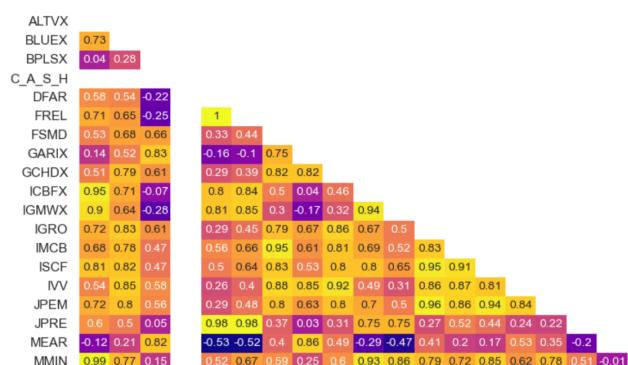
[126]:	ALTVX	BLUEX	BPLSX	C_A_S_H	DFAR	FREL	FSMD	VGCAX	VICSX	VIGI	VNQ	VO	VONG	VTEB
	Date													
2023-09-11 00:00:00	9.4000	35.2100	15.0100		1	20.7436	24.2468	33.1387	...	18.3700	20.8500	74.1083	80.8038	216.5903
1 rows × 15 columns														

```
[127]: price_df.corr()
```

[127]:	ALTVX	BLUEX	BPLSX	C_A_S_H	DFAR	FREL	FSMD	VGCAX	VICSX	VIGI	VNQ	VO	VONG	VTEB
	ALTVX	BLUEX	BPLSX	C_A_S_H	DFAR	FREL	FSMD	VGCAX	VICSX	VIGI	VNQ	VO	VONG	VTEB
ALTVX	1.0000	0.7306	0.4222	NaN	0.5828	0.7124	0.5319	...	0.9614	0.9737	0.7453	0.7125	0.7131	0.5385
BLUEX	0.7306	1.0000	0.2824	NaN	0.5420	0.6478	0.6820	...	0.7700	0.7579	0.8364	0.6497	0.8059	0.8658
BPLSX	0.4222	0.2824	1.0000	NaN	-0.2181	-0.2469	0.6561	...	-0.0097	-0.0049	0.5657	-0.2412	0.3946	0.4758
C_A_S_H	NaN	NaN	NaN	NaN	NaN	NaN	NaN	...	NaN	NaN	NaN	NaN	NaN	NaN
DFAR	0.5828	0.5420	-0.2181	NaN	1.0000	0.9979	0.3313	...	0.7299	0.6825	0.3014	0.9989	0.6128	0.2130
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...
VIGI	0.7453	0.8364	0.5657	NaN	0.3014	0.4769	0.8078	...	0.7498	0.7487	1.0000	0.4783	0.8431	0.8276
VNQ	0.7125	0.6497	-0.2412	NaN	0.9989	0.9977	0.4497	...	0.7972	0.7715	0.4783	1.0000	0.7198	0.3883
VO	0.7131	0.8059	0.3946	NaN	0.6128	0.7154	0.9256	...	0.7472	0.7257	0.8431	0.7198	1.0000	0.8135
VONG	0.5385	0.8658	0.4758	NaN	0.2130	0.3851	0.8015	...	0.5703	0.5454	0.8276	0.3883	0.8135	1.0000
VTEB	0.9368	0.7592	0.3235	NaN	0.2650	0.5005	0.6474	...	0.8698	0.8895	0.8547	0.5031	0.7293	0.6747
35 rows × 15 columns														

```
[128]: #t_df = df

plt.figure(figsize=(20,10))
mask = np.zeros_like(price_df.corr())
mask[np.triu_indices_from(mask)] = True
sns.set_style("white")
p = sns.heatmap(price_df.corr().round(2),
                 annot=True, mask=mask,
                 cmap="plasma", annot_kws={"size": 10})
```





MMIT	0.96	0.73	0.31	0.29	0.51	0.63	0.38	0.64	0.85	0.74	0.83	0.71	0.85	0.65	0.81	0.39	0.18	0.97															
PEX	0.84	0.87	0.28	0.65	0.76	0.8	0.46	0.77	0.86	0.73	0.87	0.91	0.94	0.82	0.89	0.52	0.06	0.86	0.81														
PFRAX	0.92	0.75	-0.05	0.78	0.83	0.53	0.14	0.55	0.96	0.91	0.69	0.71	0.8	0.59	0.71	0.69	-0.21	0.91	0.81	0.9													
PSAIX	0.96	0.78	0.04	0.73	0.8	0.56	0.16	0.56	0.98	0.92	0.76	0.74	0.86	0.59	0.78	0.66	-0.17	0.95	0.89	0.9	0.97												
SCHD	0.46	0.43	0.52	0.44	0.52	0.81	0.47	0.67	0.51	0.35	0.63	0.82	0.74	0.59	0.67	0.44	0.08	0.49	0.5	0.67	0.47	0.53											
SNDPX	0.93	0.73	0.33	0.21	0.46	0.63	0.41	0.63	0.81	0.69	0.82	0.69	0.82	0.66	0.79	0.37	0.24	0.95	0.99	0.79	0.78	0.85	0.46										
SWRSX	0.8	0.66	-0.35	0.85	0.89	0.26	-0.2	0.3	0.88	0.96	0.44	0.48	0.6	0.3	0.43	0.73	-0.52	0.76	0.61	0.69	0.89	0.85	0.29	0.56									
VBR	0.5	0.6	0.57	0.46	0.54	0.96	0.61	0.71	0.52	0.33	0.71	0.95	0.8	0.77	0.75	0.47	0.22	0.54	0.58	0.77	0.52	0.56	0.88	0.53	0.3								
VFIUX	0.89	0.61	-0.31	0.73	0.81	0.24	-0.19	0.29	0.93	0.99	0.48	0.46	0.62	0.27	0.48	0.62	-0.46	0.85	0.74	0.69	0.91	0.9	0.29	0.69	0.95	0.26							
VGCAX	0.96	0.77	-0.01	0.73	0.8	0.53	0.14	0.55	0.99	0.93	0.72	0.7	0.82	0.57	0.74	0.67	-0.19	0.95	0.88	0.88	0.96	0.99	0.5	0.85	0.87	0.52	0.92						
VICSX	0.97	0.76	-0	0.68	0.77	0.51	0.12	0.53	0.9	0.9	0.72	0.68	0.82	0.55	0.73	0.68	-0.18	0.97	0.9	0.86	0.96	0.99	0.48	0.87	0.86	0.49	0.93	0.99					
VIGI	0.75	0.84	0.67	0.3	0.3	0.48	0.81	0.67	0.89	0.69	0.53	0.99	0.85	0.95	0.88	0.95	0.25	0.39	0.81	0.85	0.89	0.72	0.78	0.64	0.84	0.46	0.71	0.51	0.75	0.75			
VNQ	0.71	0.65	-0.24	1	1	0.45	-0.09	0.39	0.84	0.85	0.45	0.67	0.64	0.41	0.46	0.98	-0.52	0.67	0.52	0.76	0.83	0.6	0.52	0.46	0.89	0.58	0.8	0.6	0.77	0.48			
VO	0.71	0.81	0.39	0.61	0.72	0.93	0.57	0.8	0.74	0.57	0.82	0.99	0.9	0.87	0.85	0.55	0.14	0.74	0.72	0.93	0.76	0.78	0.79	0.7	0.55	0.92	0.52	0.75	0.73	0.84	0.72		
VONG	0.54	0.87	0.48	0.21	0.39	0.8	0.81	0.87	0.49	0.32	0.81	0.81	0.74	0.98	0.79	0.17	0.52	0.61	0.63	0.8	0.6	0.58	0.44	0.65	0.32	0.67	0.29	0.57	0.55	0.83	0.39	0.81	
VTEB	0.94	0.76	0.32	0.26	0.5	0.65	0.43	0.66	0.83	0.72	0.85	0.72	0.84	0.69	0.81	0.39	0.22	0.97	0.99	0.82	0.81	0.87	0.49	0.99	0.59	0.56	0.72	0.87	0.89	0.85	0.5	0.73	0.67

## Calculate Portfolio Values

```
[129]: ## Number of Shares
```

```
[130]: shares_df = folio_df[['Ticker','Shares']]
shares_df.set_index('Ticker', drop=True, inplace=True)
shares_df['Shares'].round(0)
```

```
[130]: shares
```

Ticker	
ALTVX	106,383,0000
BLUEX	14,201,0000
BPLSX	49,967,0000
C_A_S_H	4,469,000,0000
DFAR	108,468,0000
...	...
VIGI	40,481,0000
VNQ	40,221,0000
VO	9,234,0000
VONG	41,501,0000
VTEB	20,333,0000

35 rows × 1 columns

## Prices Timeseries

```
[131]: price_df
```

```
[131]: ALTVX BLUEX BPLSX C_A_S_H DFAR FREL FSMD ... VGCAX VICSX VIGI VNQ VO VONG VTEB
```

Date	ALTVX	BLUEX	BPLSX	C_A_S_H	DFAR	FREL	FSMD	...	VGCAX	VICSX	VIGI	VNQ	VO	VONG	VTEB	
2022-01-03	10.4183	36.7510	13.1206	1	NaN	32.6081	35.1562	...	20.7575	23.9542	82.4521	107.5871	246.6520	77.9475	52.7748	
2022-01-04	10.4087	36.6256	13.3690	1	NaN	32.6081	35.4690	...	20.7382	23.9542	82.2496	107.4563	246.4671	77.1101	52.7748	
2022-01-05	10.3990	36.3122	13.4133	1	NaN	31.6710	34.6969	...	20.6996	23.8771	81.1115	104.3810	240.2957	74.6471	52.7075	
2022-01-06	10.3796	36.2943	13.4932	1	NaN	31.6900	34.9129	...	20.6610	23.8097	80.5425	104.4745	240.9089	74.4895	52.6498	
2022-01-07	10.3700	36.3480	13.5109	1	NaN	31.4912	34.6871	...	20.6225	23.7519	80.6389	103.7828	239.4682	73.6718	52.5248	
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...
2023-09-25	9.2300	34.2600	15.0000	1	19.7800	23.0400	32.2600	...	18.2200	20.6100	72.2400	76.6245	209.5800	68.9900	48.3700	
2023-09-26	9.2200	33.8200	14.8800	1	19.4100	22.6100	31.8900	...	18.2000	20.5800	71.4600	75.2281	206.6000	67.8600	48.3300	
2023-09-27	9.2000	33.8100	14.8600	1	19.2600	22.4400	32.1000	...	18.1400	20.4800	71.3000	74.7230	207.2900	67.9600	48.2400	
2023-09-28	9.1500	34.1200	14.9300	1	19.4800	22.6900	32.4350	...	18.1400	20.5100	71.6100	75.4400	208.8600	68.4800	48.0300	
2023-09-29	9.1700	33.9900	14.8200	1	19.5200	22.7500	32.2700	...	17.9500	20.4400	71.3300	75.6600	208.2400	68.4400	48.1000	

438 rows × 35 columns

```
[132]: m_df = price_df.copy()
m_df.reset_index(inplace=True)
m_df = m_df.melt(id_vars='Date')
m_df.columns = ['Date','Ticker','Price']
m_df
```

	Date	Ticker	Price
0	2022-01-03	ALTVX	10.4183
1	2022-01-04	ALTVX	10.4087
2	2022-01-05	ALTVX	10.3990
3	2022-01-06	ALTVX	10.3796
4	2022-01-07	ALTVX	10.3700
...	...	...	...
15325	2023-09-25	VTEB	48.3700
15326	2023-09-26	VTEB	48.3300
15327	2023-09-27	VTEB	48.2400
15328	2023-09-28	VTEB	48.0300
15329	2023-09-29	VTEB	48.1000

15330 rows × 3 columns

## Add Asset Classes

```
[133]: l_df = folio_df[['Ticker','Class']].drop_duplicates()
```

```
[133]: Ticker Class
```

```

0   ALTVX Interest Rate Sensitive
1   BLUEX Economically Sensitive
2   BPLSX Economically Sensitive
3   C_A_S_H Cash
4   DFAR Economically Sensitive
...
30  VIGI Economically Sensitive
31  VNQ Economically Sensitive
32  VO Economically Sensitive
33  VONG Economically Sensitive
34  VTEB Interest Rate Sensitive

```

35 rows x 2 columns

### Calculate Asset Value Overtime

```
[134]: merg_df = m_df.merge(l_df, how='left', left_on='Ticker', right_on='Ticker').merge(shares_df, how='left', left_on='Ticker', right_on='Ticker')
merg_df['share_value'] = merg_df['Price'] * merg_df['Shares']
merg_df
```

```

[134]:      Date Ticker  Price      Class    Shares  share_value
0  2022-01-03  ALTVX  10.4183  Interest Rate Sensitive  106,383.0000  1,108,334.3369
1  2022-01-04  ALTVX  10.4087  Interest Rate Sensitive  106,383.0000  1,107,305.0786
2  2022-01-05  ALTVX  10.3990  Interest Rate Sensitive  106,383.0000  1,106,276.0232
3  2022-01-06  ALTVX  10.3796  Interest Rate Sensitive  106,383.0000  1,104,217.9125
4  2022-01-07  ALTVX  10.3700  Interest Rate Sensitive  106,383.0000  1,103,188.7556
...
15325 2023-09-25  VTEB  48.3700  Interest Rate Sensitive  20,333.0000  983,507.1883
15326 2023-09-26  VTEB  48.3300  Interest Rate Sensitive  20,333.0000  982,693.9272
15327 2023-09-27  VTEB  48.2400  Interest Rate Sensitive  20,333.0000  980,863.9541
15328 2023-09-28  VTEB  48.0300  Interest Rate Sensitive  20,333.0000  976,593.9652
15329 2023-09-29  VTEB  48.1000  Interest Rate Sensitive  20,333.0000  978,017.2690

```

15330 rows x 6 columns

```
[135]: t_df = merg_df.groupby(['Date', 'Class'])[['share_value']].sum().reset_index()
```

```

[135]:      Date      Class  share_value
0  2022-01-03    Cash  4,469,000.0000
1  2022-01-03  Economically Sensitive  50,862,544.7504
2  2022-01-03  Interest Rate Sensitive  32,415,221.6159
3  2022-01-04    Cash  4,469,000.0000
4  2022-01-04  Economically Sensitive  50,981,435.3014
...
1309 2023-09-28  Economically Sensitive  48,229,242.3354
1310 2023-09-28  Interest Rate Sensitive  28,546,307.5982
1311 2023-09-29    Cash  4,469,000.0000
1312 2023-09-29  Economically Sensitive  48,193,309.1122
1313 2023-09-29  Interest Rate Sensitive  28,468,744.5006

```

1314 rows x 3 columns

```
[136]: t_df[t_df['Date'] == '2023-09-11']
```

```

[136]:      Date      Class  share_value
1269 2023-09-11    Cash  4,469,000.0000
1270 2023-09-11  Economically Sensitive  50,250,088.6926
1271 2023-09-11  Interest Rate Sensitive  28,999,975.7671

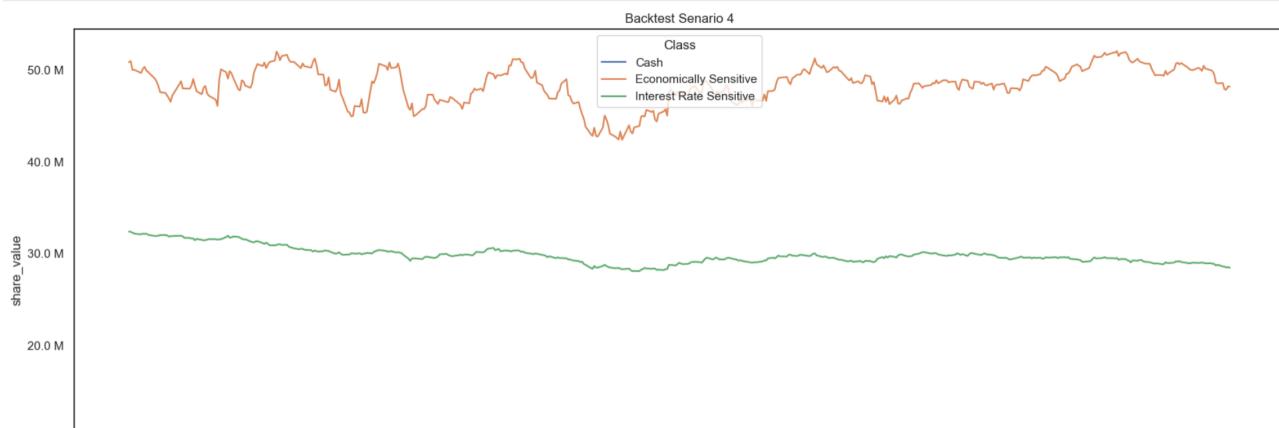
```

```

[137]: # Graph
fig, ax = plt.subplots(figsize=(20,8))
plt.ticker._label_format(style='plain', axis='y')

# Plot
sns.set_style("white")
g = sns.lineplot(data=t_df, x="Date", y="share_value", hue='Class')
g.set_yticklabels(['{:,.1f}'.format(x) + ' M' for x in g.get_yticks()/1000000])
ax.set(title='Backtest Scenario 4');

```





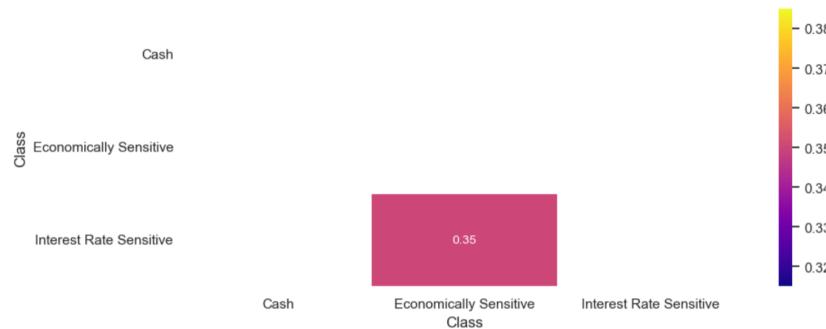
### Asset Class Correlation

```
[138]: s_df = t_df.copy()
s_df = s_df.pivot(index='Date', columns='Class', values='share_value')
s_df
```

	Class	Cash	Economically Sensitive	Interest Rate Sensitive
Date				
2022-01-03	4,469,000.0000	50,862,544.7504	32,415,221.6159	
2022-01-04	4,469,000.0000	50,981,435.3014	32,381,811.5918	
2022-01-05	4,469,000.0000	50,032,926.9210	32,289,563.2214	
2022-01-06	4,469,000.0000	50,027,840.4456	32,208,385.4021	
2022-01-07	4,469,000.0000	49,949,813.2751	32,157,512.2056	
...	...	...	...	
2023-09-25	4,469,000.0000	48,594,635.3662	28,619,242.2175	
2023-09-26	4,469,000.0000	47,913,704.2044	28,593,708.2587	
2023-09-27	4,469,000.0000	47,864,633.1783	28,502,372.2289	
2023-09-28	4,469,000.0000	48,229,242.3354	28,546,307.5982	
2023-09-29	4,469,000.0000	48,193,309.1122	28,468,744.5006	

438 rows × 3 columns

```
[139]: plt.figure(figsize=(10,4))
mask = np.zeros_like(s_df.corr())
mask[np.triu_indices_from(mask)] = True
sns.set_style("white")
_p = sns.heatmap(s_df.corr().round(2), annot=True, mask=mask, cmap="plasma", annot_kws={"size": 10})
```



### Calculate VaR

```
[140]: l2 = list(folio_df['Ticker'])
l1 = percent_df.columns
list_dif = set(l2).symmetric_difference(set(l1))

print('l1: ', len(l1), 'l2: ', len(l2), 'dif: ', list_dif)
l1: 35 l2: 35 dif: set()
```

```
[141]: var = VaR(percent_df, weights, alpha=[0.05, 0.025, 0.01])
#var = VaR(percent_df, weights, alpha=0.05)
var
```

```
[141]: <VaR - μ: -0.03%, σ: 0.7151%, Portfolio σ: 0.7159%>
```

```
[142]: var.info
```

```
[142]: {'Daily Mean PnL': -0.00025741804339413863,
'Daily Volatility': 0.007150601883874462,
'Portfolio Volatility': 0.0071587974188095016}
```

```
[143]: var.historic()
```

	VaR(95.0)	VaR(97.5)	VaR(99.0)	CVaR(95.0)	CVaR(97.5)	CVaR(99.0)	CDaR(95.0)	CDaR(97.5)	CDaR(99.0)
2023-09-29	-0.0123	-0.0148	-0.0180	-0.0158	-0.0184	-0.0216	-0.1772	-0.1835	-0.1862

```
[144]: print('VaR(95.0):', var.historic()['VaR(95.0)'][0]*100)
print('Portfolio VaR(95.0)', var.historic()['VaR(95.0)'][0]*portfolio_total*1000)

VaR(95.0): -1.2315075343638227
Portfolio VaR(95.0) -1031005.7926940487
```

```
[145]: var.parametric()
```

	VaR(95.0)	VaR(97.5)	VaR(99.0)	CVaR(95.0)	CVaR(97.5)	CVaR(99.0)	CDaR(95.0)	CDaR(97.5)	CDaR(99.0)
2023-09-29	-0.0238	-0.0252	-0.0269	-0.0289	-0.0289	-0.0289	-0.1772	-0.1835	-0.1862

```
[146]: print('VaR(95.0):', var.parametric()['VaR(95.0)'][0]*100)
print('Portfolio VaR(95.0)', var.parametric()['VaR(95.0)'][0]*portfolio_total*1000)

VaR(95.0): -2.3813632315321978
Portfolio VaR(95.0) -1993653.4838064406
```

```
[147]: var.monte_carlo()
```

	VaR(95.0)	VaR(97.5)	VaR(99.0)	CVaR(95.0)	CVaR(97.5)	CVaR(99.0)	CDaR(95.0)	CDaR(97.5)	CDaR(99.0)
2023-09-29	-0.0120	-0.0143	-0.0170	-0.0151	-0.0171	-0.0195	-0.1772	-0.1835	-0.1862

```
[148]: print('VaR(95.0):', var.monte_carlo()['VaR(95.0)'][0]*100)
```

```

print('Portfolio VaR(95.0)', var.monte_carlo()['VaR(95.0)'][0]*portfolio_total*1000)
VaR(95.0): -1.1991295392246542
Portfolio VaR(95.0) -1008330.0855807732

[149]: var.monte_carlo(stressed=True)

[149]:
  VaR(95.0)  VaR(97.5)  VaR(99.0)  CVaR(95.0)  CVaR(97.5)  CVaR(99.0)  CDaR(95.0)  CDaR(97.5)  CDaR(99.0)
2023-09-29 -0.0181 -0.0195 -0.0210 -0.0199 -0.0210 -0.0222 -0.04974 -0.05025 -0.05057

```

## Backtest

```

[150]: bth = var.backtest(method='h')
Backtest: Historic Method: 100%|██████████| 187/187 [00:00<00:00, 3105.94it/s]

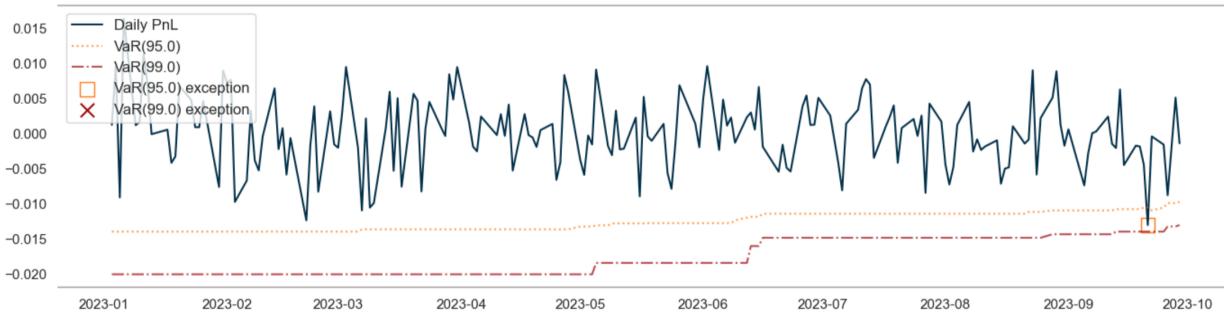
[151]: var.evaluate(bth)

[151]:
    Amount  Percent  Mean Deviation  STD Deviation  Min Deviation  Max Deviation
Observations      187       1             0              0             0             0
VaR(95.0)        1   0.0053        -0.0025        0.0000       -0.0025       -0.0025
VaR(99.0)        0   0.0000          NaN           NaN           NaN           NaN
CVaR(95.0)       1   0.0053        -0.0005        0.0000       -0.0005       -0.0005
CVaR(99.0)       0   0.0000          NaN           NaN           NaN           NaN
CDaR(95.0)       0   0.0000          0             0             0             0
CDaR(99.0)       0   0.0000          0             0             0             0

```

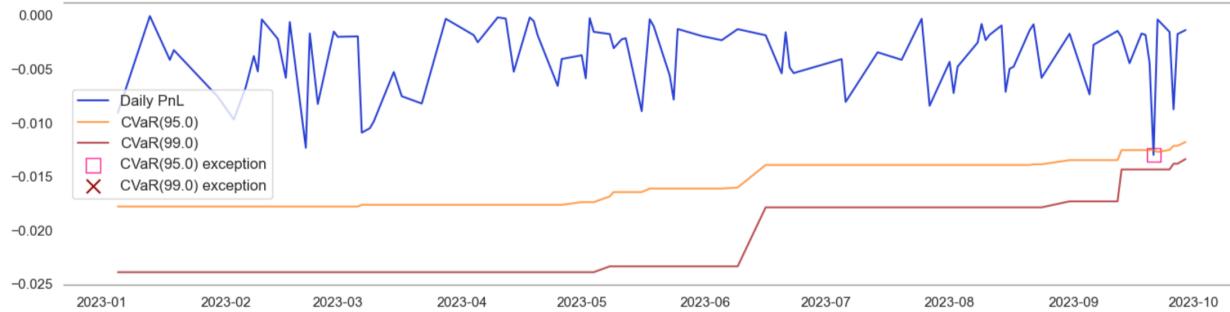
```
[152]: var.var_plot(bth)
```

Historic VaR Backtest



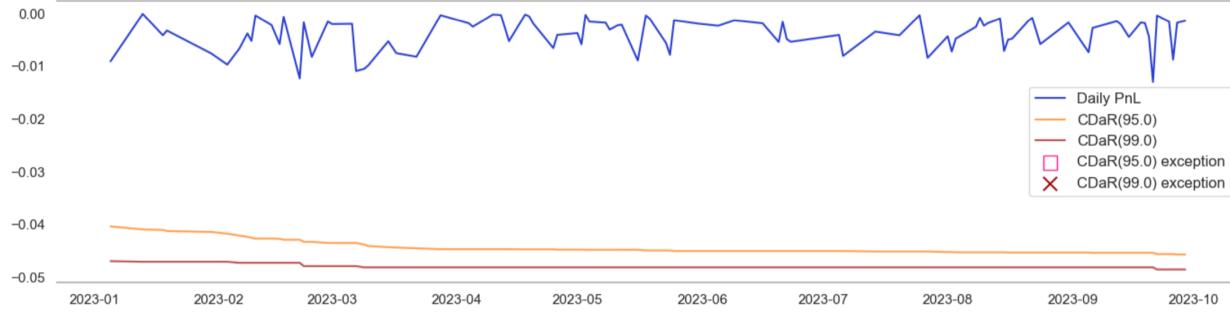
```
[153]: var.cvar_plot(bth)
```

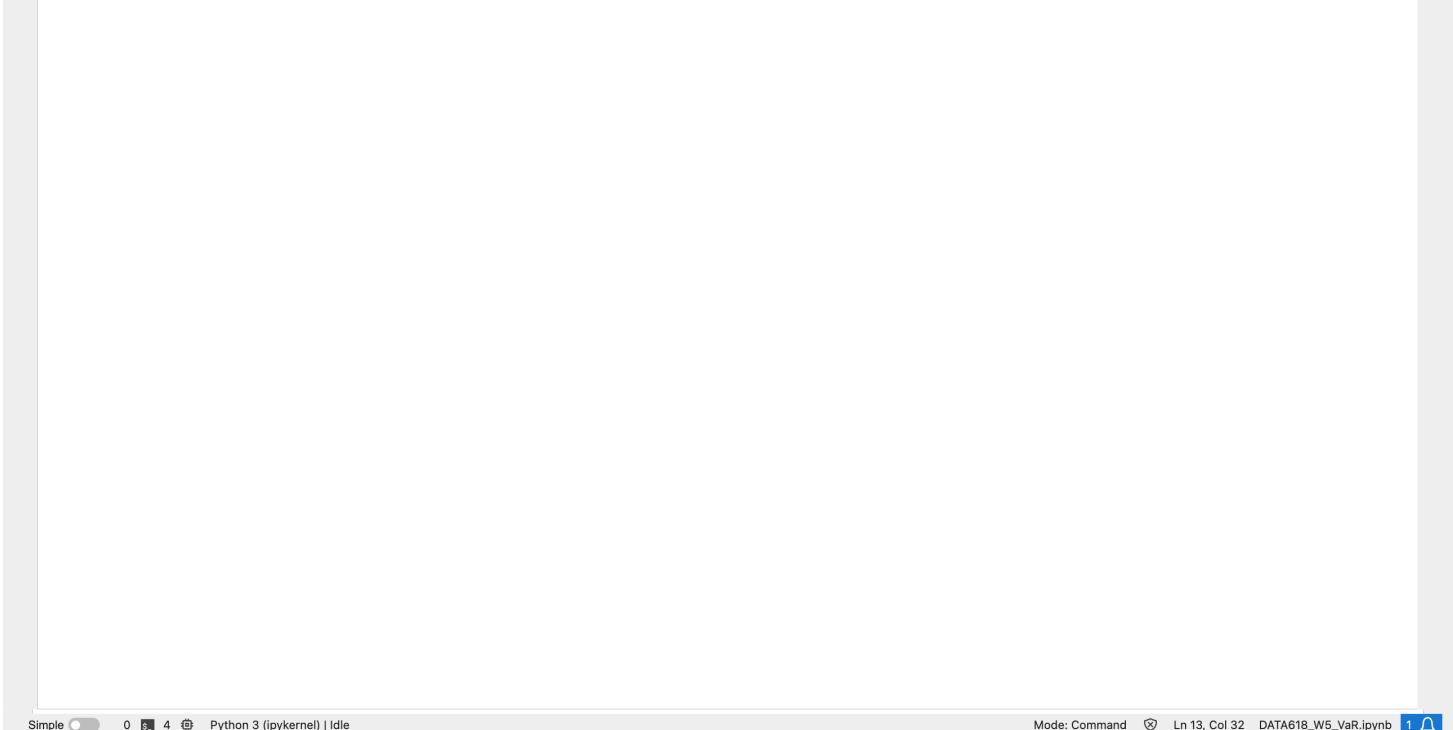
Historic CVaR Backtest



```
[154]: var.cdar_plot(bth)
```

Historic CDaR Backtest





Simple 0 4 Python 3 (ipykernel) | Idle

Mode: Command Ln 13, Col 32 DATA618\_W5\_VaR.ipynb 1 ⚡