GROUP WORK PROJECT # __1_
GROUP NUMBER: _____3793_______

MScFE 560: FINANCIAL MARKETS

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Remember: Any group members who did **not contribute to the project should be given all zero (0) points for the collaboration grade on the GWP submission page.*

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Use the box below to explain any attempts to reach out to a non-contributing member. Type (N/A) if all members contributed. **Note:** You may be required to provide proof of your outreach to non-contributing members upon request.

MScFE 560 FINANCIAL MARKETS

Group Work Project # 1

Student Group 3793

Irgibay Jemissov, Boyan Davidov, Ebenezer Yeboah

Portfolio A from Irgibay Jemissov

Step 1

For Portfolio A (Buy 1 asset and short 1 asset) the following intsrumens has been choosen: Treasury Yield 10 Years (yahoo ticker: "^TNX") and Bitcoin USD (yahoo ticker: "BTC-USD") as a short asset. Those instruments were choosen, as they have different nature and suppose to have negative correlation and different risks, which could make portfolio be more diversified.

As a timeline 1-year period has been used for calculation, with daily changes data.

In [2]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import yfinance as yf
import statistics as ST
from datetime import datetime
from pandas_datareader import data as pdr
import seaborn as sns
from scipy.optimize import minimize
```

Analysis of US Treasury Bond 10Y

In [3]:
```
start = datetime(2022, 7, 24)
end = datetime(2023, 7, 24)

yf.pdr_override()
TBond = pdr.get_data_yahoo('TN=F', start, end).fillna(0)
```

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

In [4]:
```
TBond.head()
```

Out[4]:

Date	Open	High	Low	Close	Adj Close	Volume
2022-07-25	130.015625	130.015625	128.984375	129.281250	129.281250	192676
2022-07-26	129.515625	130.546875	129.390625	129.656250	129.656250	231779
2022-07-27	129.406250	130.390625	129.296875	130.250000	130.250000	261005
2022-07-28	129.625000	131.218750	129.203125	130.796875	130.796875	347332
2022-07-29	130.812500	131.515625	130.265625	131.250000	131.250000	386139

In [5]:

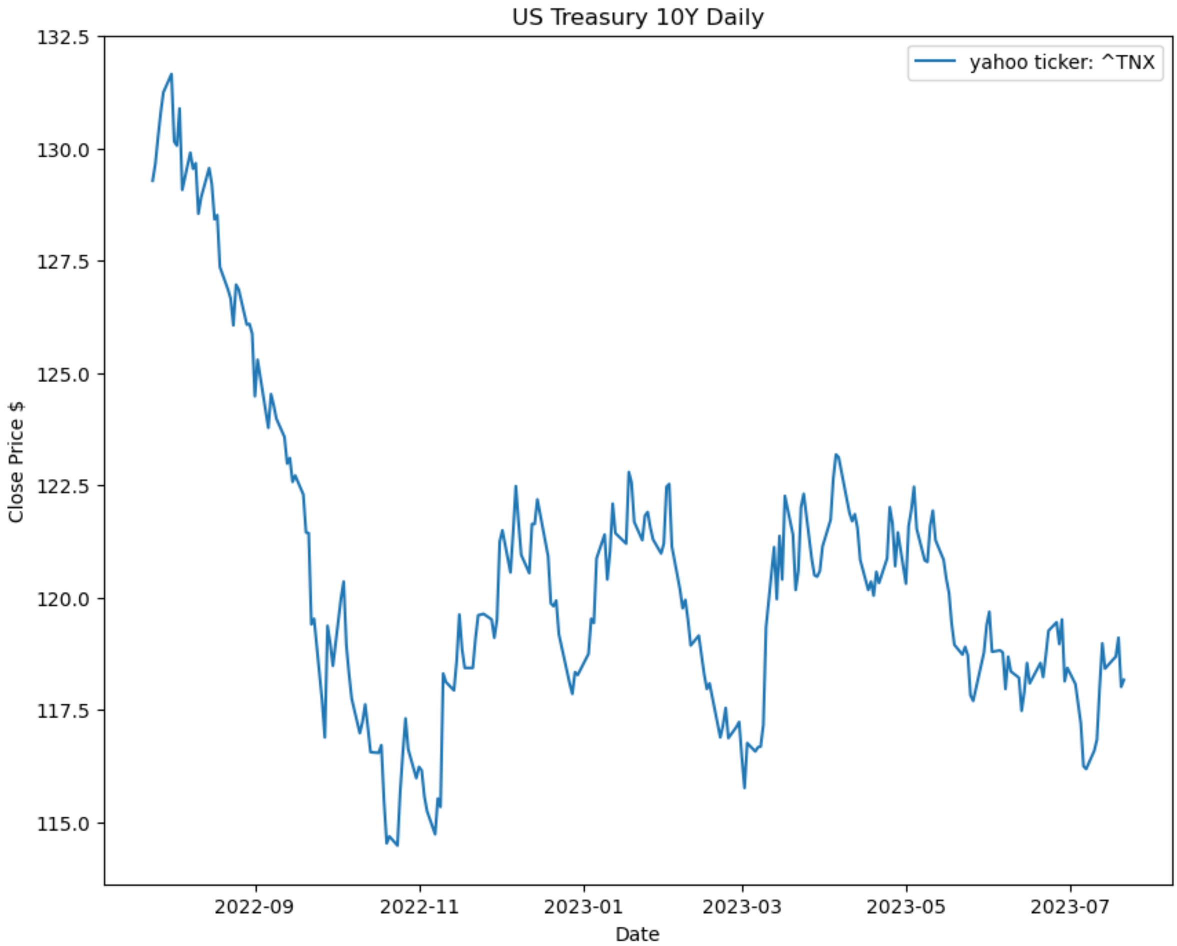
```
#as the timeseries represent yield we simply need to subtract previous day from cur
TBond['Return'] = -(((TBond['Close']-TBond['Close'].shift(1))/TBond['Close'].shift
TBond.head()
```

Out[5]:

Date	Open	High	Low	Close	Adj Close	Volume	Return
2022-07-25	130.015625	130.015625	128.984375	129.281250	129.281250	192676	NaN
2022-07-26	129.515625	130.546875	129.390625	129.656250	129.656250	231779	-0.290065
2022-07-27	129.406250	130.390625	129.296875	130.250000	130.250000	261005	-0.457942
2022-07-28	129.625000	131.218750	129.203125	130.796875	130.796875	347332	-0.419866
2022-07-29	130.812500	131.515625	130.265625	131.250000	131.250000	386139	-0.346434

In [6]:

```
plt.figure(figsize=(10, 8))
plt.plot(TBond.index, TBond['Close'], label='yahoo ticker: ^TNX')
plt.xlabel('Date')
plt.ylabel('Close Price $')
plt.title('US Treasury 10Y Daily')
plt.legend()
plt.show()
```



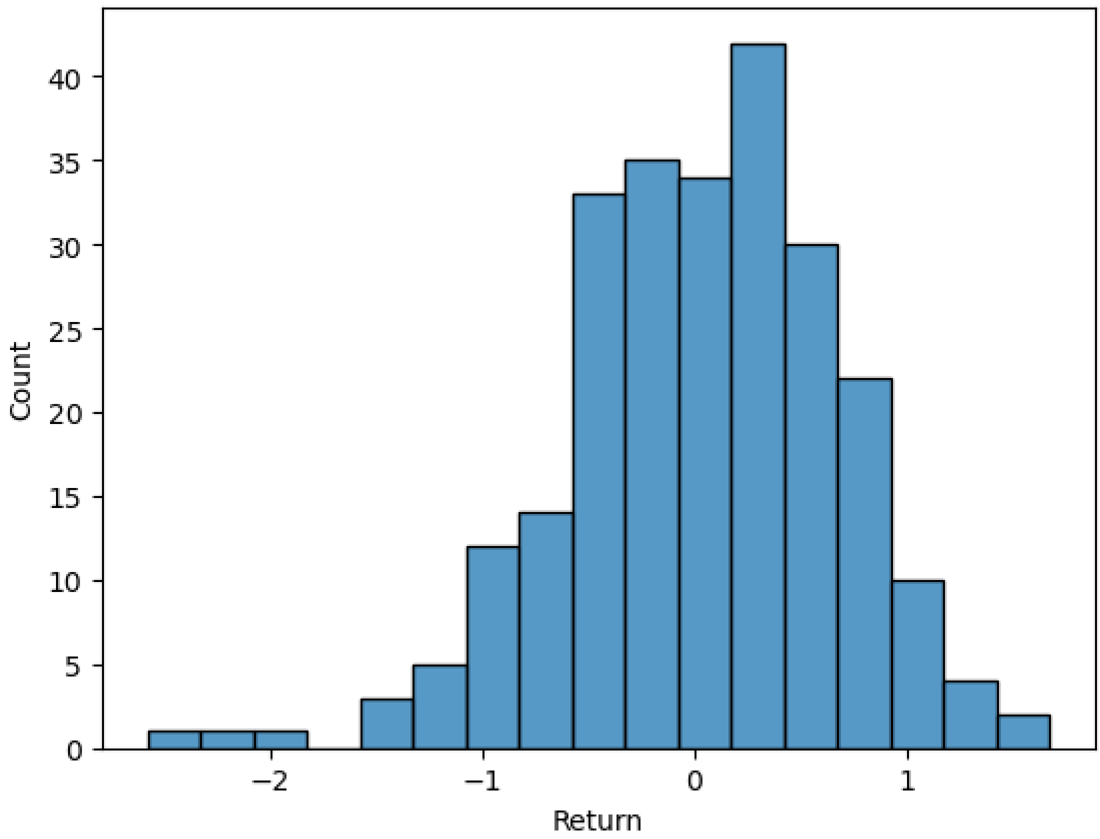
The US Treasury Bond 10 Y has trend to increase and for financial markets expected to be stable.

In [7]:
```
TBond_mean = round(TBond['Return'].mean(),3)
TBond_std = round(TBond['Return'].std(),3)
TBond_skew = round(TBond['Return'].skew(),3)
TBond_kurt = round(TBond['Return'].kurt(),3)
```

In [8]:
```
print("TBond_mean = ",TBond_mean)
print("TBond_std = ",TBond_std)
print("TBond_skew = ",TBond_skew)
print("TBond_kurt = ",TBond_kurt)
```

```
TBond_mean =  0.034
TBond_std =  0.643
TBond_skew =  -0.532
TBond_kurt =  1.025
```

In [9]:
```
TBond_dstr = sns.histplot(TBond["Return"])
```



In [10]:
```
TBond_ROI = round((np.log(TBond['Close'][-1]/TBond['Close'][0])*100),2)
```

In [11]:
```
print("TBond Year Return =", TBond_ROI, "%")
```

```
TBond Year Return = -8.99 %
```

Analysis of Bitcoin

Bitcoin will be used for shorting, as it suppose to have more volatility.

In [12]:
```
start = datetime(2022, 7, 24)
end = datetime(2023, 7, 24)

yf.pdr_override()
BTC = pdr.get_data_yahoo('BTC-USD', start, end).fillna(0)
```

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

In [13]:
```
BTC.head()
```

Out[13]:

Date	Open	High	Low	Close	Adj Close	Volume
2022-07-24	22465.509766	22974.001953	22306.839844	22609.164062	22609.164062	23565495303
2022-07-25	22607.156250	22649.121094	21361.642578	21361.701172	21361.701172	35574561406
2022-07-26	21361.121094	21361.121094	20776.816406	21239.753906	21239.753906	28624673855
2022-07-27	21244.169922	22986.529297	21070.806641	22930.548828	22930.548828	31758955233
2022-07-28	22933.640625	24110.470703	22722.265625	23843.886719	23843.886719	40212386158

In [14]:

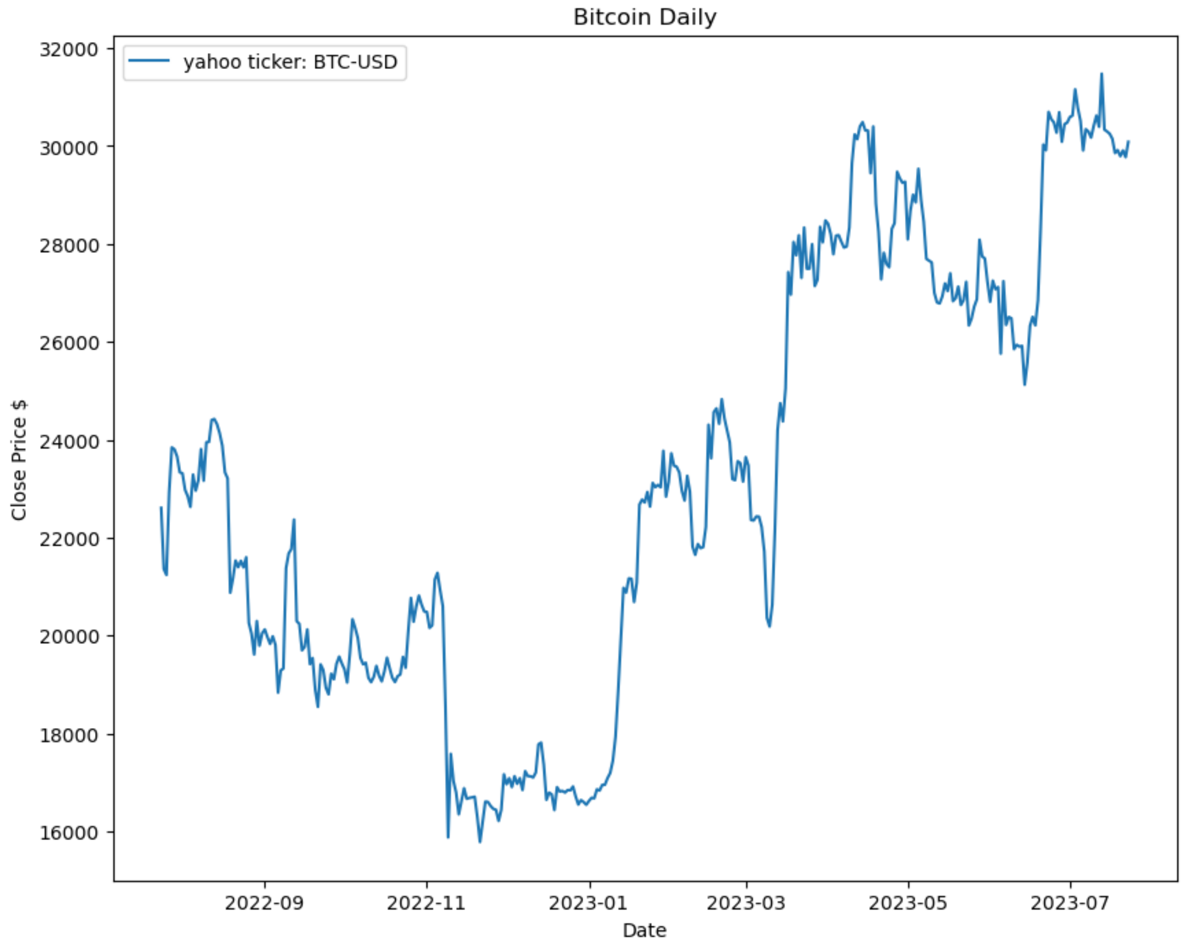
```
ReturnB = (((BTC['Close']-BTC['Close'].shift(1))/BTC['Close'].shift(1))*100)
BTC.insert(loc = 4, column = "Return", value = ReturnB)
BTC.head()
```

Out[14]:

Date	Open	High	Low	Close	Return	Adj Close	Volu
2022-07-24	22465.509766	22974.001953	22306.839844	22609.164062	NaN	22609.164062	23565495
2022-07-25	22607.156250	22649.121094	21361.642578	21361.701172	-5.517510	21361.701172	35574561
2022-07-26	21361.121094	21361.121094	20776.816406	21239.753906	-0.570869	21239.753906	28624673
2022-07-27	21244.169922	22986.529297	21070.806641	22930.548828	7.960520	22930.548828	31758955
2022-07-28	22933.640625	24110.470703	22722.265625	23843.886719	3.983062	23843.886719	40212386

In [15]:

```
plt.figure(figsize=(10, 8))
plt.plot(BTC.index, BTC['Close'], label='yahoo ticker: BTC-USD')
plt.xlabel('Date')
plt.ylabel('Close Price $')
plt.title('Bitcoin Daily')
plt.legend()
plt.show()
```

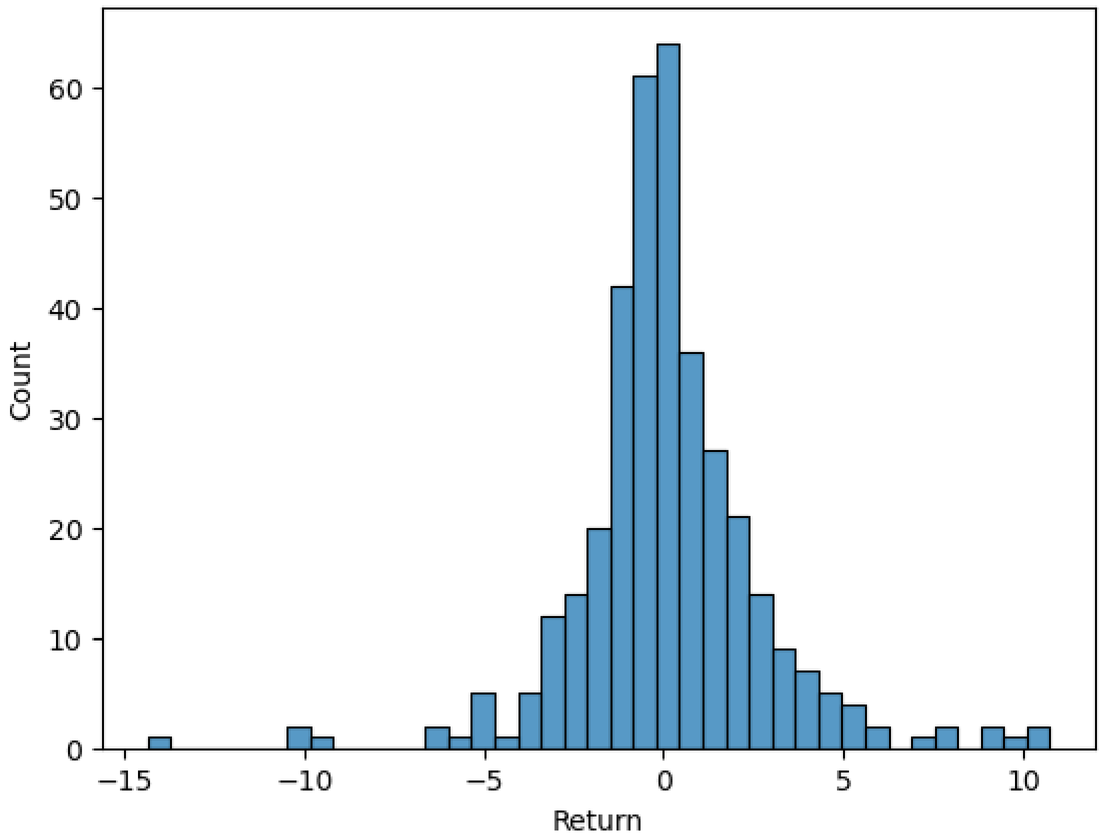


In [16]:
```
BTC_mean = round(BTC['Return'].mean(),3)
BTC_std = round(BTC['Return'].std(),3)
BTC_skew = round(BTC['Return'].skew(),3)
BTC_kurt = round(BTC['Return'].kurt(),3)
```

In [17]:
```
print("BTC_mean = ",BTC_mean)
print("BTC_std = ",BTC_std)
print("BTC_skew = ",BTC_skew)
print("BTC_kurt = ",BTC_kurt)
```

```
BTC_mean =  0.114
BTC_std =  2.66
BTC_skew =  0.008
BTC_kurt =  5.432
```

In [18]:
```
BTC_dstr = sns.histplot(BTC["Return"])
```



In [19]:
```
BTC_ROI = round((np.log(BTC['Close'][-1]/BTC['Close'][0])*100),2)
```

In [20]:
```
print("Bitcoin Year Return =", BTC_ROI, "%")
```

```
Bitcoin Year Return = 28.57 %
```

Correlation matrix and covariance matrix

In [21]:
```
Portfolio_df = pd.DataFrame(({"TBond": TBond["Return"],"BTC": BTC["Return"]})).fil
Portfolio_df.head()
```

Out[21]:

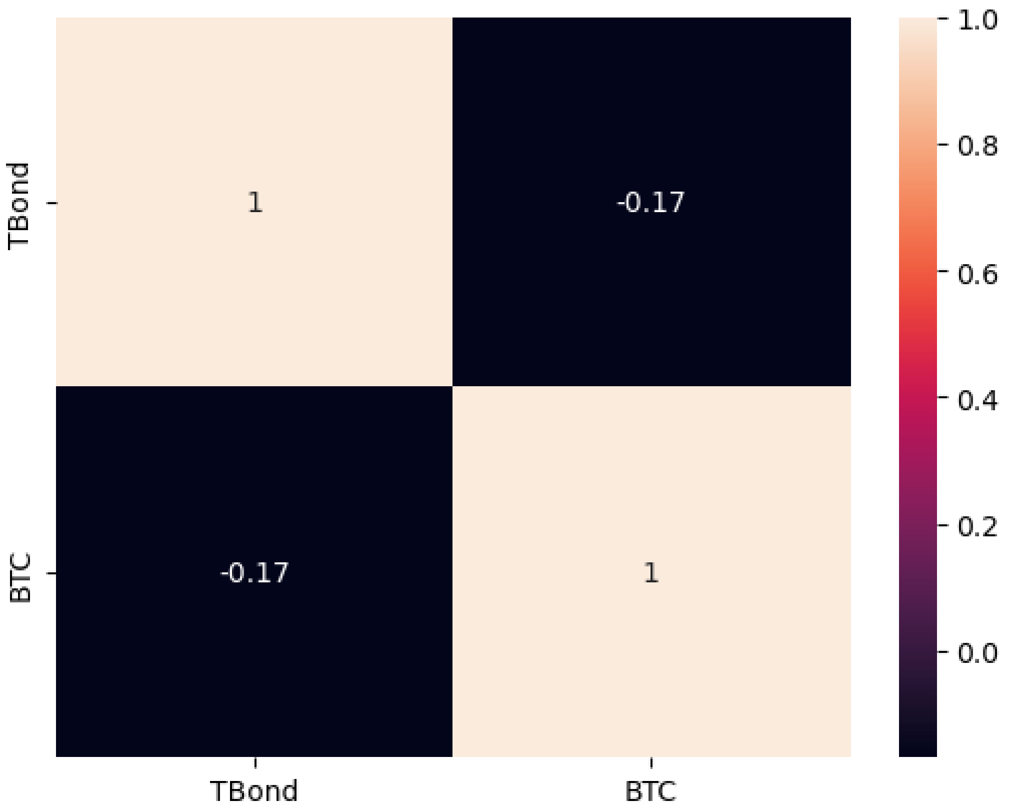
	TBond	BTC
Date		
2022-07-24	0.000000	0.000000
2022-07-25	0.000000	-5.517510
2022-07-26	-0.290065	-0.570869
2022-07-27	-0.457942	7.960520
2022-07-28	-0.419866	3.983062

In [22]:
```
Corr_matrix = Portfolio_df.corr()
Corr_matrix
```

Out[22]:

	TBond	BTC
TBond	1.00000	-0.16843
BTC	-0.16843	1.00000

In [23]:
```
sns.heatmap(Corr_matrix, annot=True)
plt.show()
```



Portfolio Return and Volatility

Before we will start to calculate portfolio return and volatility, we should determine the weights of each instrument in whole portolio. For simplification and for this assignment assumption of the equal portfolio distribution has been made.

In [24]:
```
weights = np.array([1,-1])
```

In [25]:
```
Portfolio_stat = pd.DataFrame(({"TBond": TBond["Return"],"BTC": BTC["Return"]})).d
```

In [26]:
```
Portfolio_stat.head()
```

Out[26]:

	TBond	BTC
Date		
2022-07-26	-0.290065	-0.570869
2022-07-27	-0.457942	7.960520
2022-07-28	-0.419866	3.983062
2022-07-29	-0.346434	-0.164629
2022-08-01	-0.309524	-0.097259

In [27]:
```
Portfolio_stat['Portfolio_return'] = Portfolio_stat['TBond'] * weights[0] + Portfo
portfolio_std_dev = np.std(Portfolio_stat['Portfolio_return'])
portfolio_var = portfolio_std_dev**2
```

In [28]:
```
portfolio_var
```
Out[28]:
```
10.241140941380973
```
In [29]:
```
print("Portfolio return = ",Portfolio_stat['Portfolio_return'].sum())
print("Portfolio volatility = ",portfolio_std_dev)
```
```
Portfolio return =  -26.481360353259923
Portfolio volatility =  3.200178267125282
```

Step 2

1. Shorting

a.

This porfolio could be sold short, but US Treasury is not good for short trading. At the same time Bitcoin is a good instrument to be sold short.

b.

Shorting is the strategy when you borrow financial asstet that you do not own and you expect that price will drop. Basic mechanism of shorting consist of several steps.

1. You borrow financial instrument
2. Sell it when price is high to a third party,
3. There intermidiate payments for original owner, as we should compensate all fees on instrument and some extra fees
4. Covering short - it means that you wait till price will drop and buy back the instrument
5. Return security to original owner In shorting your gain is the difference between Selling price and Buy Back purchasing price and minus all dividens, fees which you should compensate to the owner.

2. Credit Risk

a.

Yes portfolio has a credit risk, but it is limited as there is risk-free instrument - US Treasury 10Y

b.

The credit risk for Bitcoin as a cryptocurrency is that the price could fall down, and you will be unable to use it as payment instrument. For US Treasury 10Y it is supposed that no credit risk applies, as it is issued and confirmed by the Government.

3. Portfolio Statistic

In [30]:
```
print("Portfolio return = ",Portfolio_stat['Portfolio_return'].sum())
print("Portfolio volatility = ",portfolio_std_dev)
```

```
Portfolio return =  -26.481360353259923
Portfolio volatility =  3.200178267125282
```

4.Diversification

a.

Those two instruments has negative correlation between each other -0.015196. It means they will compesate each other in case of volatility.

b.

Yes, portfolio is well diversified. One of the instruments (US Treasury Bond 10Y) is a risk-free instrument, and has negative correlation with Bitcoin. Bincoin is volatile and it is good for short position

5. Comparing Portfolios

Portfolio	Return (%)	Volatility (%)
A	-26.48	3.2
B	2.48	0.47
C	-28	1.36

Portfolio A has less negative return over the 1-year holding period but it is the most volatile. The short leg in bitcoin has clearly affected the performance and added its extreme volatility.

6. Assessing Risk

a.

US Treasury 10Y bond is a risk free instrument. Both instruments could be infuelnced by geopolitical and economical situations. Current events in 2020 (COVID-19) and in 2022 (Russia-Ukrain conflict) show that such events has significants infulence on the market. Specially such events are difficult fo forecast thus could be considered as oulayers. For Bitcoin tighter regulation may have negative impact. Also such events as change in methodology of mining as it was in Fall 2022 could have significant impact. The price has fall, but when supply decreased as most of the players become out of the market price increased.

b.

Similar events will infulence on both instruments, even for risk free, as it only depends on Basic Interest confirmed by US Government

7. Perfomance

a.

Recovery of the economy will have positive impact on those financial instruments.

b.

Portfolio could be increased if US Treasury will decrease Basic Rate, and this which have higher rate will be efficient. This will be connected with growth of US economy. Currently many of the production companies has moved to US, thus means cash inflow to US economy which is good. For Bitcoin perfomance will be increased in case of more Governments will accept Bitcoin as a verified payment method, and demand will increase.

8. Distrupters

a.

If central bank will change Basic Interest it could influence on US Treasury bonds, but only in situation you want to sell them. As new Bonds will have different interests. For Bitcoin, as it is not regulated (mostly) there is no direct influence, but as Bitcoin have positive correlations with some markets (e.g. SP500 SPDR ETF) it could be infulence too.

b.

Investments banks could influence on Bitcoin, as their decision to invest or not to invest on it could change the price.

9. Re-assessing Risk

a.

No, they have different skew

b.

Instrument have negative correlation, which means they have hedge each other and compensate risks.

MScFE 560 FINANCIAL MARKETS

Group Work Project # 1

Student Group 3793

Irgibay Jemissov, Boyan Davidov, Ebenezer Yeboah

Portfolio B from Ebenezer Yaboah

STEP 1

In [62]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import yfinance as yf
from datetime import datetime
from pandas_datareader import data as pdr
import seaborn as sns
```

The composition of Portfolio B is Investment

1. Income Stock - Deutsche Telekom (DTE.DE)
2. Bond - Boxx $ Inv Grade Corporate Bond ETF (LQD)

We analyze 1-year holding period.

Deutsche Telekom (DTE.DE)

In [63]:
```
start = datetime(2022, 7, 24)
end = datetime(2023, 7, 24)

yf.pdr_override()
data_equity = pdr.get_data_yahoo('DTE.DE', start, end)
```

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

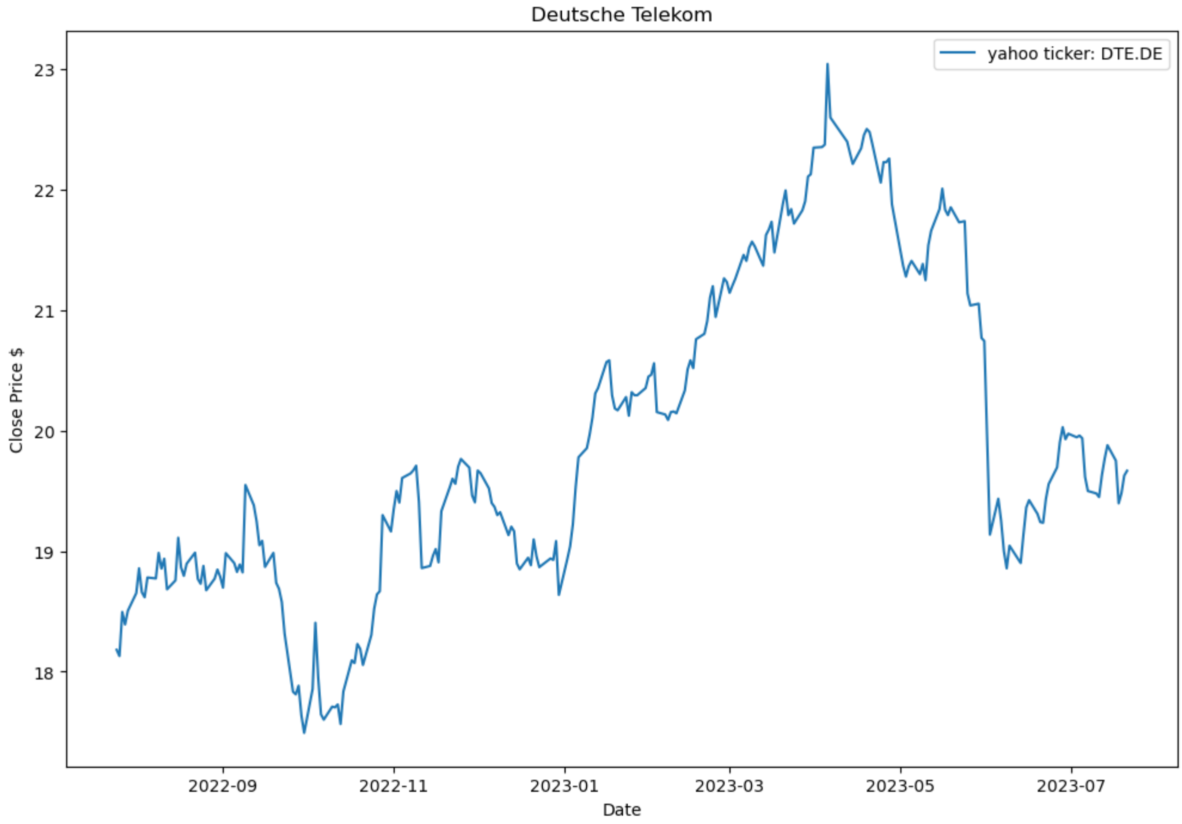
In [64]:
```
data_equity.head(3)
```

Out[64]:

Date	Open	High	Low	Close	Adj Close	Volume
2022-07-25	18.080000	18.459999	18.052000	18.181999	17.629715	7429260
2022-07-26	18.087999	18.129999	17.948000	18.129999	17.579294	7278770
2022-07-27	18.143999	18.577999	17.926001	18.496000	17.934177	10665757

In [65]:
```
plt.figure(figsize=(12, 8))
plt.plot(data_equity.index, data_equity['Close'], label='yahoo ticker: DTE.DE')
plt.xlabel('Date')
```

```
plt.ylabel('Close Price $')
plt.title('Deutsche Telekom')
plt.legend()
plt.show()
```



In [66]:
```
#compute returns in percentage
data_equity['Return'] = data_equity['Close'].pct_change()*100
```

In [67]:
```
data_equity.sample()
```

Out[67]:

	Open	High	Low	Close	Adj Close	Volume	Return
Date							
2023-01-10	19.950001	20.035	19.832001	19.969999	19.363403	6544697	0.574126

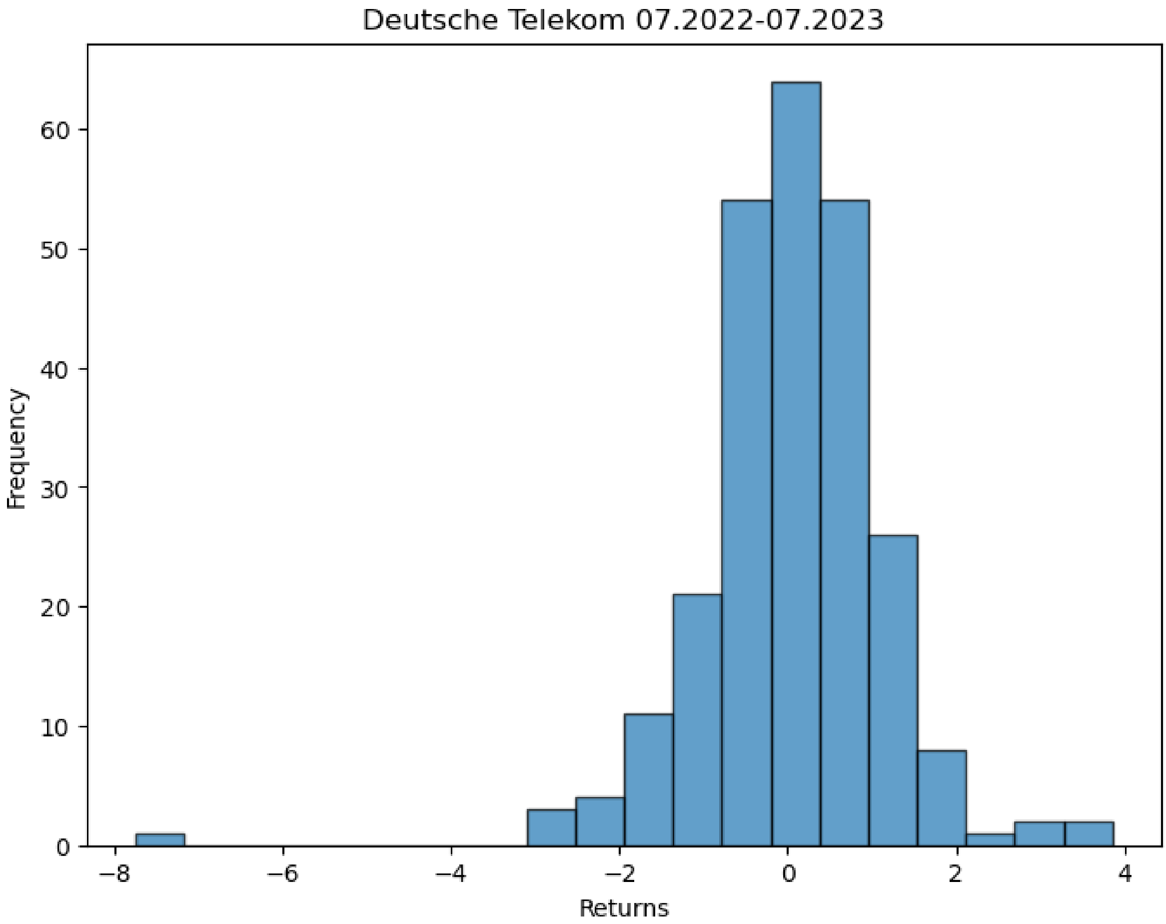
In [68]:
```
stock_mean = round(data_equity['Return'].mean(),3)
stock_std = round(data_equity['Return'].std(),3)
stock_skew = round(data_equity['Return'].skew(),3)
stock_kurt = round(data_equity['Return'].kurt(),3)
```

In [69]:
```
print("\033[1mAverage Return in %:\033[0m", stock_mean)
print("\033[1mStandard Deviation:\033[0m", stock_std)
print("\033[1mSkewness:\033[0m", stock_skew)
print("\033[1mKurtosis:\033[0m", stock_kurt)
```

```
Average Return in %: 0.037
Standard Deviation: 1.105
Skewness: -1.253
Kurtosis: 10.009
```

In [70]:
```
plt.figure(figsize=(8, 6))
plt.hist(data_equity['Return'].dropna(), bins=20, edgecolor='black', alpha=0.7)
plt.xlabel('Returns')
plt.ylabel('Frequency')
```

```
plt.title('Deutsche Telekom 07.2022-07.2023')
plt.show()
```



The distribution looks normal, however, from the skewness we can see it is assymetric with left skew as there was one day of extremely negative return due to news about T-Mobile US (subsidiary of Deutsche Telekom). Kurtosis is also very high due to that.

In [71]:
```
year_return_equity = np.log(data_equity['Close'][-1]/data_equity['Close'][0])
```

In [72]:
```
"{:.0%}".format(year_return_equity)
```

Out[72]:
```
'8%'
```

Boxx $ Inv Grade Corporate Bond ETF (LQD)

We take bond ETF that is portfolio of investment grade bonds. This is much easier than finding timeseries for single entity and provides additional diversification.

In [73]:
```
start = datetime(2022, 7, 24)
end = datetime(2023, 7, 24)

yf.pdr_override()
data_bondETF = pdr.get_data_yahoo('LQD', start, end)
```

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

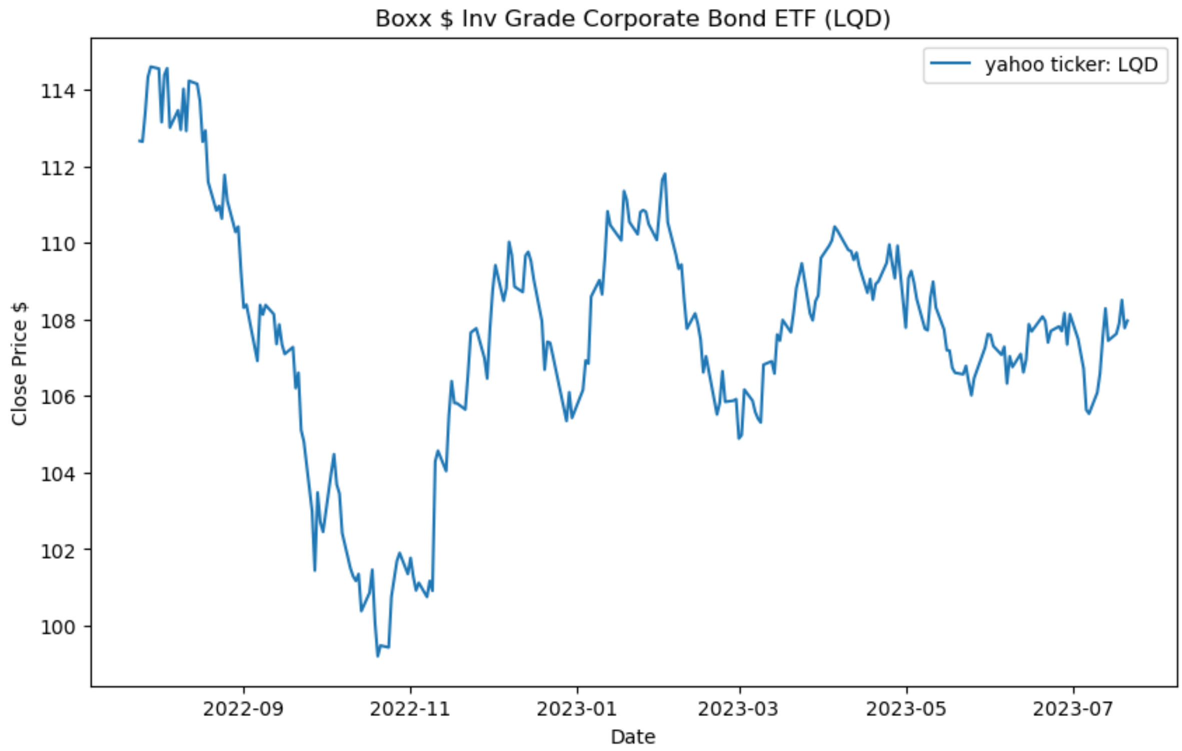
In [74]:
```
data_bondETF.head(3)
```

Out[74]:

Date	Open	High	Low	Close	Adj Close	Volume
2022-07-25	112.839996	113.010002	112.400002	112.669998	108.539688	25656700
2022-07-26	113.010002	113.120003	112.599998	112.650002	108.520432	18514600
2022-07-27	113.160004	114.050003	113.129997	113.400002	109.242935	16995200

In [75]:

```
# Plot the time series data
plt.figure(figsize=(10, 6))
plt.plot(data_bondETF.index, data_bondETF['Close'], label='yahoo ticker: LQD')
plt.xlabel('Date')
plt.ylabel('Close Price $')
plt.title('Boxx $ Inv Grade Corporate Bond ETF (LQD)')
plt.legend()
plt.show()
```



In [76]:

```
data_bondETF['Return'] = data_bondETF['Close'].pct_change()*100
```

In [77]:

```
bond_mean = round(data_bondETF['Return'].mean(),3)
bond_std = round(data_bondETF['Return'].std(),3)
bond_skew = round(data_bondETF['Return'].skew(),3)
bond_kurt = round(data_bondETF['Return'].kurt(),3)
```

In [78]:

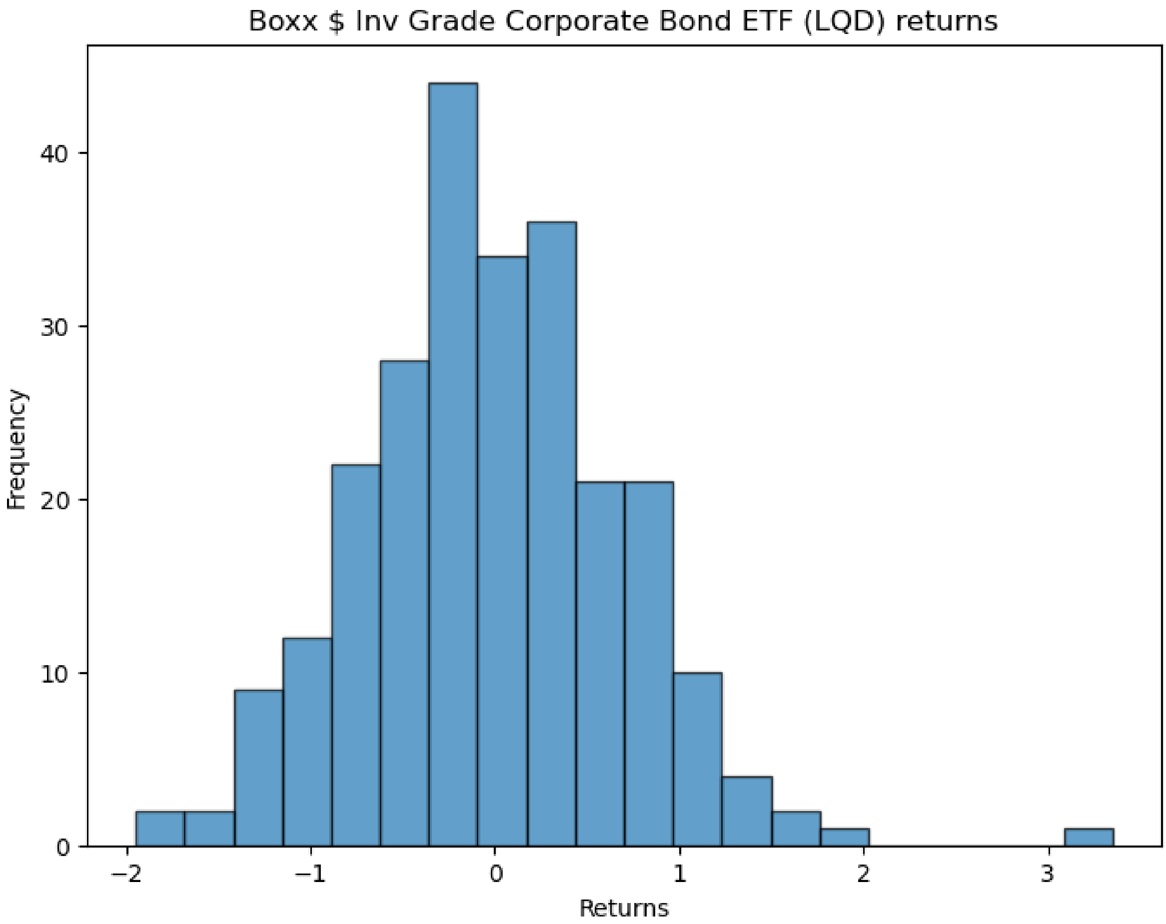
```
print("\033[1mAverage Return in %:\033[0m", bond_mean)
print("\033[1mStandard Deviation:\033[0m", bond_std)
print("\033[1mSkewness:\033[0m", bond_skew)
print("\033[1mKurtosis:\033[0m", bond_kurt)
```

```
Average Return in %: -0.015
Standard Deviation: 0.707
Skewness: 0.432
Kurtosis: 1.575
```

In [79]:

```
plt.figure(figsize=(8, 6))
plt.hist(data_bondETF['Return'].dropna(), bins=20, edgecolor='black', alpha=0.7)
plt.xlabel('Returns')
```

```
plt.ylabel('Frequency')
plt.title('Boxx $ Inv Grade Corporate Bond ETF (LQD) returns')
plt.show()
```



This is still assymetric but right skewed which is good feature. Kurtosis is less than 3 implying thin tails and less risk of abnormal returns.

In [80]:
```
year_return_bond = np.log(data_bondETF['Close'][-1]/data_bondETF['Close'][0])
```

In [81]:
```
"{:.0%}".format(year_return_bond)
```

Out[81]:
```
'-4%'
```

Step 2

Shorting

a.

Yes, the portfolio can be sold short. Shorting is a financial strategy in which an investor borrows an asset (such as a stock or bond) from a broker and sells it on the open market with the expectation that its price will decline.

b.

To engage in short selling, the investor will first borrow the assets from their broker and then proceed to sell them at the current market prices. The cash proceeds from the sales will be held in the brokerage account. The investor will aim to close the short positions by buying back the same quantity of assets they initially borrowed and sold, hoping to do so at a lower price and then return it to their broker.

Credit Risk

Yes, the portfolio has credit risk. The credit risk in this portfolio relates to the potential that the issuers of the bonds may encounter financial difficulties and be unable to meet its interest payment or principal repayment obligations. Also the ETF issuer might be in risk of default.

Portfolio Statistics

a.

We assume equally weighted portfolio of 2 assets. The portfolio return is (using 1-year log return)

In [82]:
```
round(((0.5)*year_return_equity+(0.5)*year_return_bond),3)
```

Out[82]:
```
0.018
```

b.

In [83]:
```
weights = np.array([0.5,0.5])
```

In [84]:
```
Portfolio_stat = pd.DataFrame({
    'Equity': data_equity['Return'],
    'Bond ETF': data_bondETF['Return']
})

Portfolio_stat = Portfolio_stat.dropna()
```

In [85]:
```
Portfolio_stat
```

Out[85]:

Date	Equity	Bond ETF
2022-07-26	-0.285997	-0.017748
2022-07-27	2.018760	0.665779
2022-07-28	-0.562284	0.828920
2022-07-29	0.619836	0.236142
2022-08-01	0.788933	-0.043629
...	...	...
2023-07-17	-0.643855	0.167520
2023-07-18	-1.792224	0.250863
2023-07-19	0.433032	0.565339
2023-07-20	0.749409	-0.672752
2023-07-21	0.203785	0.176287

243 rows × 2 columns

In [86]:

```
Portfolio_stat['Portfolio_return'] = data_equity['Return'] * weights[0] + data_bon
Portfolio_stat = Portfolio_stat.dropna()
portfolio_std_dev = np.std(Portfolio_stat['Portfolio_return'])
portfolio_var = portfolio_std_dev**2
```

In [87]:

```
Portfolio_stat.head(3)
```

Out[87]:

Date	Equity	Bond ETF	Portfolio_return
2022-07-26	-0.285997	-0.017748	-0.151873
2022-07-27	2.018760	0.665779	1.342269
2022-07-28	-0.562284	0.828920	0.133318

In [88]:

```
print("Portfolio return = ",Portfolio_stat['Portfolio_return'].sum())
print("Portfolio variance = ", portfolio_var)
print("Portfolio volatility = ",portfolio_std_dev)
```

```
Portfolio return =  2.4885855508945975
Portfolio variance =  0.4782206572382351
Portfolio volatility =  0.6915350007325985
```

Diversification

a.

The diversification between the two assets is seen to be an average one. Both assets, the bond and the income stock, have different characteristics, such as average returns, volatilities, skewness, and kurtosis. The bond exhibits a slightly negative average return with low volatility, while the income stock has a neutral average return with higher volatility.

b.

Considering a very low volatility and correlation (0.21), I can argue that the portfolio is well diversified

In [89]:
```
correlation = data_bondETF['Return'].corr(data_equity['Return'])
correlation
```

Out[89]:
```
0.1163160526298384
```

Comparing Portfolios

Portfolio	Return (%)	Volatility (%)
A	-26.48	3.2
B	2.48	0.47
C	-28	1.36

In terms of risk, this portfolio has the least risk as it has the least standard deviation which measures the volatility of the portfolio from the returns. This indicates that the portfolio is less risky. The average return of the income stock which forms part of the portfolio is less negative compared to short bitcoin and stocks. It averages the bonds giving us a relatively higher average return compared to the other portfolios

Assessing Risk

a.

Consider the income stock is a technology company. If the government imposes stricter regulations on the technology sector, it could affect the technology company's growth and profits. This could include more scrutiny on data privacy, content moderation, or monopolistic practices, which may result in fines, limited operations, or fewer users engaging with the company's services. Assuming the bonds are also issued by a Real Estate Investment Company, during a recession, both the technology company and the Real Estate Investment Company might see less spending from consumers and lower demand for what they offer. The technology sector could have fewer funds for IT projects, and the real estate market may see property values and occupancy rates go down.

b.

Events like recession or increased market competition could potentially affect both assets in the portfolio. During a recession, demand for technology products and services might decrease, impacting the technology company's earnings. At the same time, the real estate sector may experience slower property sales or lower rental income. However, some events may have a greater impact on one asset compared to the other. For example, increased regulatory scrutiny could disproportionately affect the technology company if it becomes the subject of investigations. On the other hand, the Real Estate Company may be less impacted by such regulations.

Performance

a.

Rising digitalization and the growing shift towards remote work may result in greater demand for the telecom company's software, cloud services, and digital platforms. This surge in adoption could lead to improved financial performance and overall success for the company.

Low Interest Rates: A period of low interest rates might make the investment grade bonds more attractive to investors seeking stable income, as they offer relatively safer yields compared to other fixed-income assets.

b.

Mostly, both benefit from similar events but the impact differs. For instance: Risk-off environment would primarily benefit the investment grade bonds by making them more appealing to investors seeking fixed-income instruments with stable returns. Technological advancements and increased digitalization (favorable economic conditions) would directly enhance the growth prospects and stock performance of the technology company.

Disrupters

a.

Changes in interest rates by the central bank can have a significant impact on the portfolio's performance. If interest rates go up, bond prices may fall, affecting the value of the bonds in the portfolio. On the other hand, if interest rates go down, assets like bonds and real estate, which are sensitive to interest rates, may perform better.

b.

Investment banks can offer research reports and recommendations on specific securities or industries. These suggestions may influence portfolio managers' choices to purchase, sell, or hold particular assets. This will go a long way to affect the price or value of the security.

Re-assessing Risk

a.

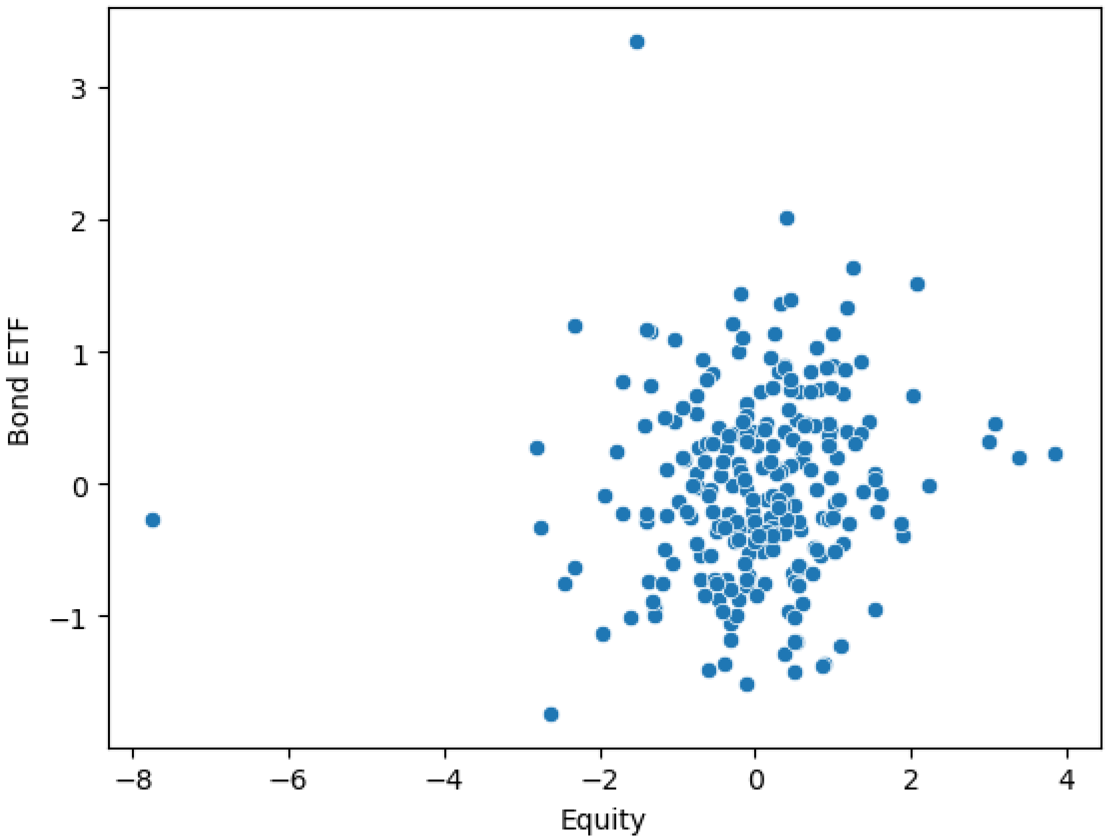
No, the investment in the portfolio do not have the same skew. The good thing is one is left skewed whereas the other is right skewed, so combined together would imply less risk than on stand-alone basis. b) There is a weak positive correlation considering a correlation of 0.22

b.

From the plots below it seems that the three assets are uncorellated with the exception of bitcoin and equity appear to be slightly positively correlated. It is not clear whether any non-linear relationship exists.

In [90]:
```
sns.scatterplot(x=Portfolio_stat['Equity'],y=Portfolio_stat['Bond ETF'])
```

Out[90]: <Axes: xlabel='Equity', ylabel='Bond ETF'>



MScFE 560 FINANCIAL MARKETS

Group Work Project # 1

Student Group 3793

Irgibay Jemissov, Boyan Davidov, Ebenezer Yeboah

Portfolio C from Boyan Davidov

STEP 1

In [1]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import yfinance as yf
from datetime import datetime
from pandas_datareader import data as pdr
import seaborn as sns
```

For Portfolio C we have chosen the following positions:

- Bying Xtrackers ShortDAX Daily ETF (XSDX.L)
- Buying iShares 1-3 Year Treasury Bond ETF (yahoo ticker: SHY)
- Buying Short Bitcoin Strategy ETF ((yahoo ticker: BITI)

We have short exposure to equities and bitcoin. Our long leg is U.S. treasuries.

For the analysis we take 1-year timeseries. We assume that we are retail investor and as such we are constrained when short-selling instruments. We prefer ETFs/ETNs as we can't buy/sell directly from stock exchanges, plus - we don't want to provide excessive cash as margin for derivatives.

Xtrackers ShortDAX Daily ETF

Xtrackers ShortDAX Daily ETF (XSDX.L) is inversely tracking the performance of large and mid-size German companies (like Siemens AG, Deutsche Telekom AG, SAP AG, major european car producers like BMW, Mercedes and Volkswagen as well as).

In [2]:
```
start = datetime(2022, 7, 24)
end = datetime(2023, 7, 24)

yf.pdr_override()
data_equityIndex = pdr.get_data_yahoo('XSDX.L', start, end)
```

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

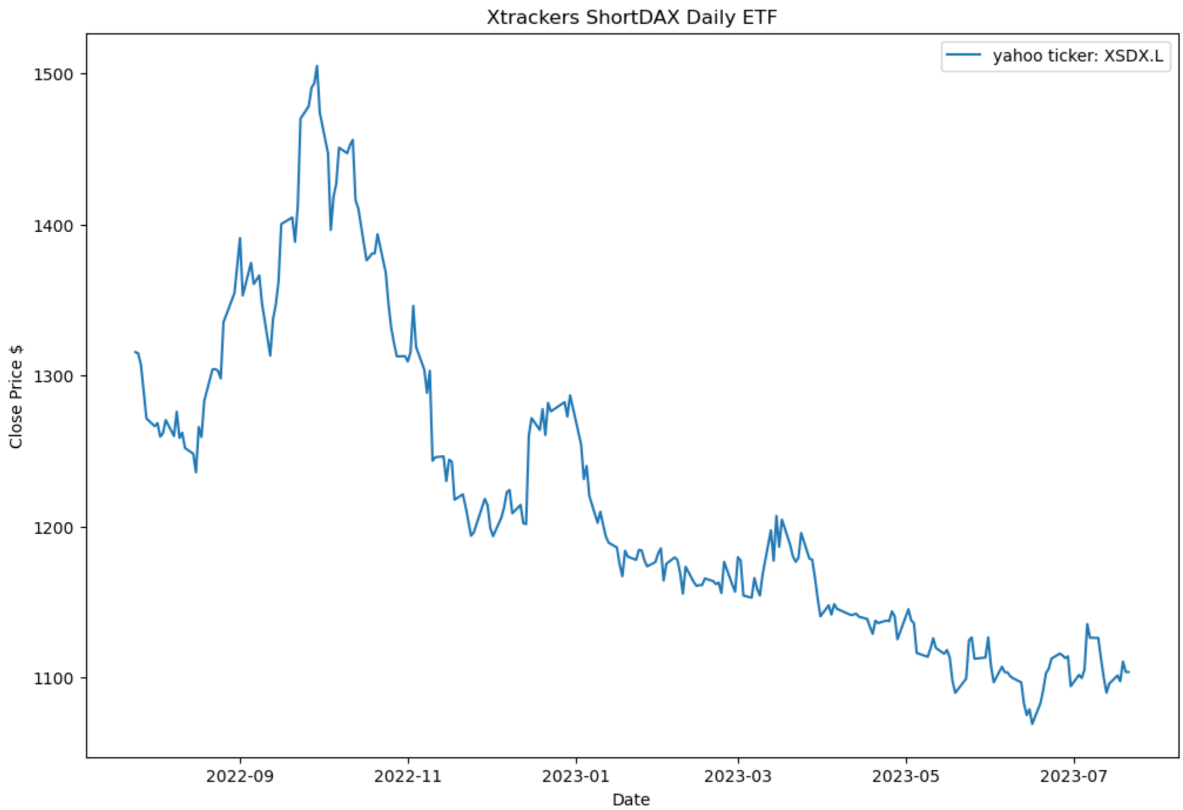
In [3]:
```
data_equityIndex.head(3)
```

Out[3]:

Date	Open	High	Low	Close	Adj Close	Volume
2022-07-25	1316.000000	1316.000000	1316.000000	1315.500000	1315.500000	227
2022-07-26	1319.599976	1322.564941	1315.199951	1314.599976	1314.599976	3551
2022-07-27	1313.199951	1313.199951	1307.790039	1306.900024	1306.900024	1824

In [4]:

```
plt.figure(figsize=(12, 8))
plt.plot(data_equityIndex.index, data_equityIndex['Close'], label='yahoo ticker: X
plt.xlabel('Date')
plt.ylabel('Close Price $')
plt.title('Xtrackers ShortDAX Daily ETF')
plt.legend()
plt.show()
```



DAX has bottomed in mid October 2022 and since then it has been trending up almost incessantly. Not surprinsigly the inverse tracker is trending down. Currently the index is trending in range and this level seems pivotal for further movements. Let's compute the first 4 moments of the returns distribution for the past year

In [5]:

```
#these can be computed much more efficiently using the libraries but I believe we s
#respective formulae
def compute_moments(time_series):
    # Compute returns using the formula: (current_Close - previous_Close) / previou
    time_series['Return'] = ((time_series['Close'] - time_series['Close'].shift(1)
    returns = time_series['Return'].dropna()

    #average return
    mean_returns = np.mean(returns)

    # st.deviation
    st_deviation = np.sqrt(np.sum((returns - mean_returns)**2) / (len(returns) - 1
```

```python
    # skewness
    skewness = (np.sum((returns - mean_returns)**3) / len(returns)) / (st_deviatio

    #kurtosis
    kurtosis = (np.sum((returns - mean_returns)**4) / len(returns)) / (st_deviatio

    return round(mean_returns,3), round(st_deviation, 3), round(skewness, 3), roun
```

In [6]:

```python
# Compute the reauired metrics
av_returns_equity, st_deviation_equity, skewness_equity, kurtosis_equity = compute_
```

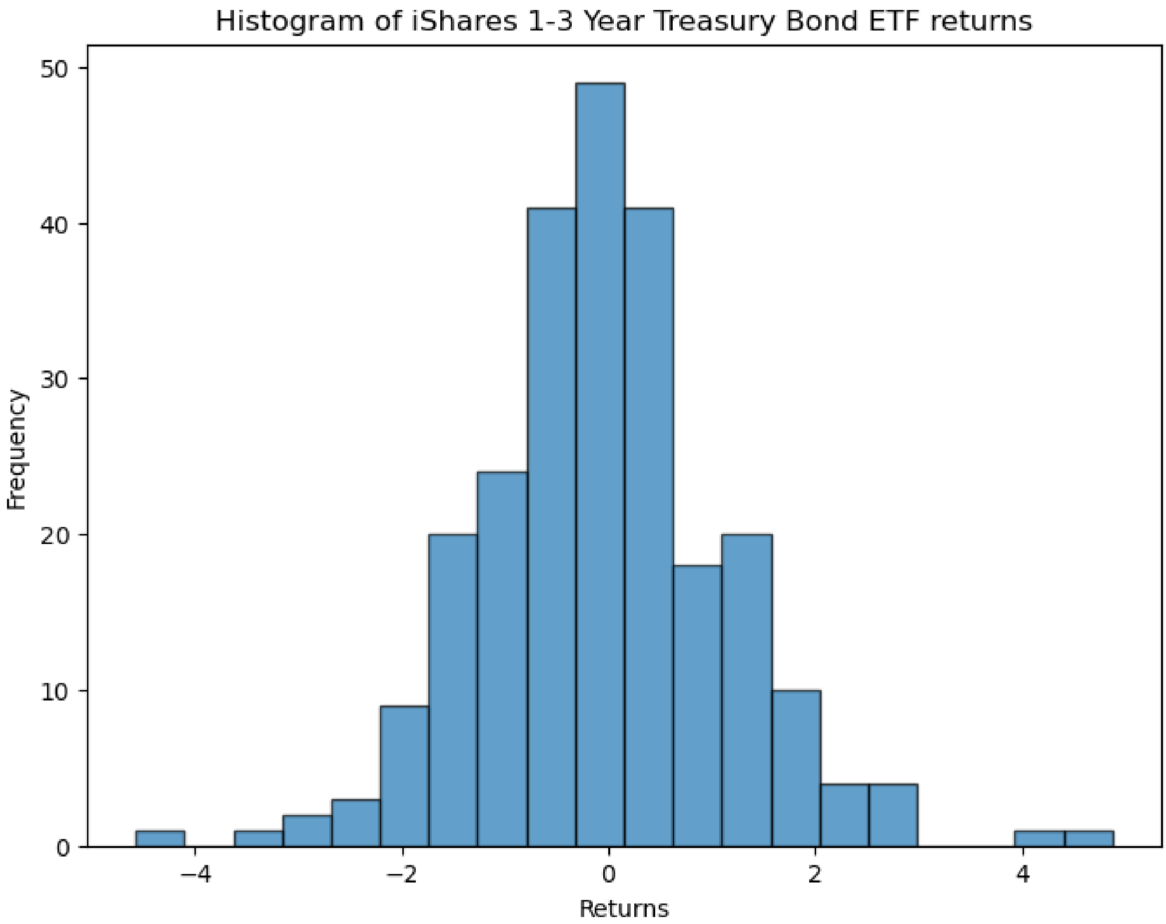
In [7]:

```python
print("\033[1mAverage Return in %:\033[0m", av_returns_equity)
print("\033[1mStandard Deviation:\033[0m", st_deviation_equity)
print("\033[1mSkewness:\033[0m", skewness_equity)
print("\033[1mKurtosis:\033[0m", kurtosis_equity)
```

Average Return in %: -0.063
Standard Deviation: 1.201
Skewness: 0.266
Kurtosis: 1.752

In [8]:

```python
plt.figure(figsize=(8, 6))
plt.hist(data_equityIndex['Return'].dropna(), bins=20, edgecolor='black', alpha=0.
plt.xlabel('Returns')
plt.ylabel('Frequency')
plt.title('Histogram of iShares 1-3 Year Treasury Bond ETF returns')
plt.show()
```



The distribution looks normal, however, from the 3rd and 4th moment we can see that the returns were right skewed (skewness>0 implying assymetry) and with thin tails (i.e. platykurtic since kurtosis < 3). These characteristics are extremely good for risky assets - they imply:

- **right skewness** - higher probability of substantial positive return rather than negative
- **thin tails** - less risk as extreme negative returns are less likely

However, the 1-year return is -18%

In [9]:
```
year_return_shortequity = np.log(data_equityIndex['Close'][-1]/data_equityIndex['C
```

In [10]:
```
"{:.0%}".format(year_return_shortequity)
```

Out[10]:
```
'-18%'
```

iShares 1-3 Year Treasury Bond ETF

iShares 1-3 Year Treasury Bond ETF (yahoo ticker: SHY) as the name suggests invests in short-term U.S. treasuries. We choose to invest in ETF as it offers better mixture to government bonds rather than buying single bond.

In [11]:
```
start = datetime(2022, 7, 24)
end = datetime(2023, 7, 24)

yf.pdr_override()
data_bondETF = pdr.get_data_yahoo('SHY', start, end)
```

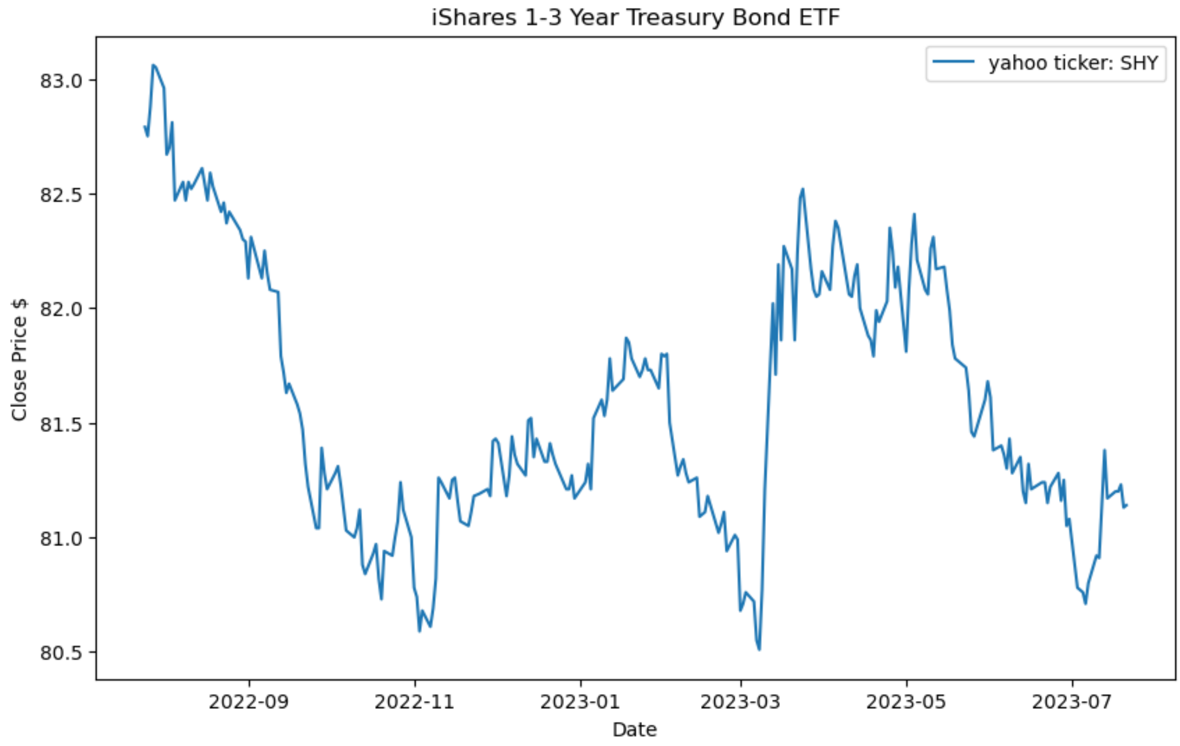
```
[*********************100%***********************]  1 of 1 completed
```

In [12]:
```
data_bondETF.head(3)
```

Out[12]:

Date	Open	High	Low	Close	Adj Close	Volume
2022-07-25	82.790001	82.830002	82.769997	82.790001	80.912292	20449500
2022-07-26	82.870003	82.879997	82.750000	82.750000	80.873192	2854600
2022-07-27	82.769997	82.910004	82.730003	82.879997	81.000237	7051600

In [13]:
```
# Plot the time series data
plt.figure(figsize=(10, 6))
plt.plot(data_bondETF.index, data_bondETF['Close'], label='yahoo ticker: SHY')
plt.xlabel('Date')
plt.ylabel('Close Price $')
plt.title('iShares 1-3 Year Treasury Bond ETF')
plt.legend()
plt.show()
```

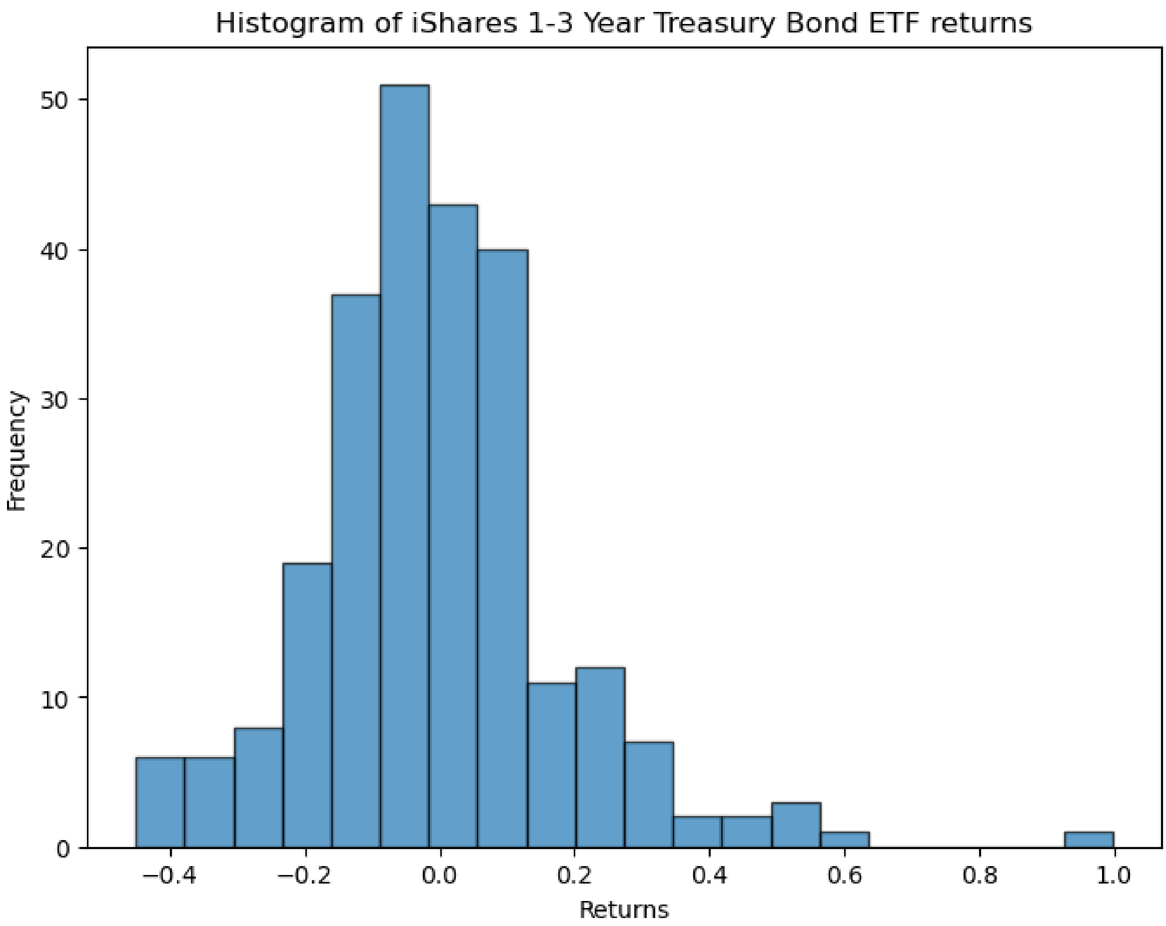


In [14]:
```
av_returns_bond, st_deviation_bond, skewness_bond, kurtosis_bond = compute_moments
```

In [15]:
```
print("\033[1mAverage Return in %:\033[0m", av_returns_bond)
print("\033[1mStandard Deviation:\033[0m", st_deviation_bond)
print("\033[1mSkewness:\033[0m", skewness_bond)
print("\033[1mKurtosis:\033[0m", kurtosis_bond)
```

Average Return in %: -0.008
Standard Deviation: 0.186
Skewness: 0.915
Kurtosis: 3.562

In [16]:
```
plt.figure(figsize=(8, 6))
plt.hist(data_bondETF['Return'].dropna(), bins=20, edgecolor='black', alpha=0.7)
plt.xlabel('Returns')
plt.ylabel('Frequency')
plt.title('Histogram of iShares 1-3 Year Treasury Bond ETF returns')
plt.show()
```



This is still assymetric and the kurtosis is slightly higher than 3, yet the closest to normal distribution from the instruments we chose for the portfolio. The one year return is -2%

In [17]:
```
year_return_bond = np.log(data_bondETF['Close'][-1]/data_bondETF['Close'][0])
```

In [18]:
```
"{:.0%}".format(year_return_bond)
```

Out[18]:
```
'-2%'
```

Short Bitcoin Strategy ETF

Short Bitcoin Strategy ETF (yahoo ticker: BITI doesn't mean we are shorting the ETF. In fact, it is inverse tracker of bitcoin, meaning we can buy the ETF and profit when bitcoin prices fall.

In [19]:
```
start = datetime(2022, 7, 24)
end = datetime(2023, 7, 24)

yf.pdr_override()
data_bitcoinETF = pdr.get_data_yahoo('BITI', start, end)
```

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

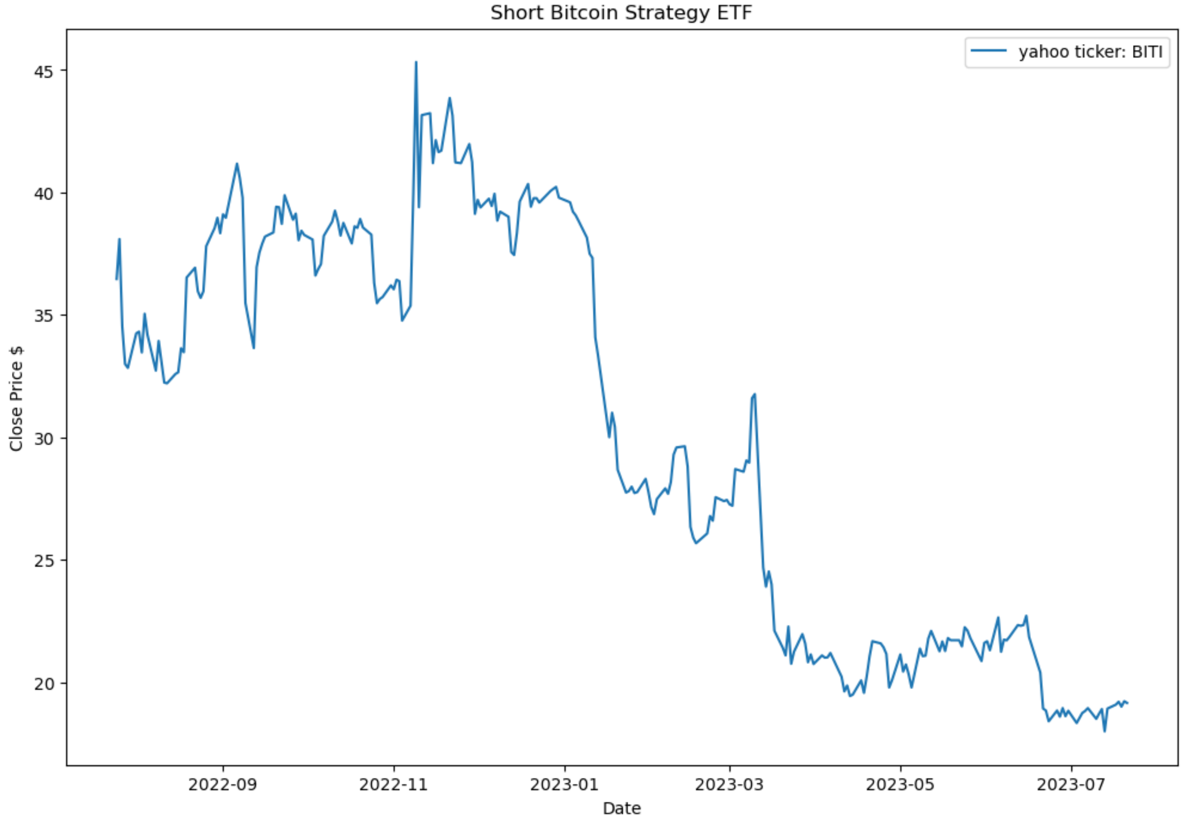
In [20]:
```
data_bitcoinETF.head(3)
```

Out[20]:

Date	Open	High	Low	Close	Adj Close	Volume
2022-07-25	36.340000	36.910000	36.209999	36.470001	36.289776	633000
2022-07-26	38.040001	38.380001	37.810001	38.099998	37.911716	629800
2022-07-27	37.380001	37.389999	34.054001	34.529999	34.359360	648200

In [21]:

```
plt.figure(figsize=(12, 8))
plt.plot(data_bitcoinETF.index, data_bitcoinETF['Close'], label='yahoo ticker: BITI
plt.xlabel('Date')
plt.ylabel('Close Price $')
plt.title('Short Bitcoin Strategy ETF')
plt.legend()
plt.show()
```



In [22]:

```
av_returns_bitcoin, st_deviation_bitcoin, skewness_bitcoin, kurtosis_bitcoin = com
```

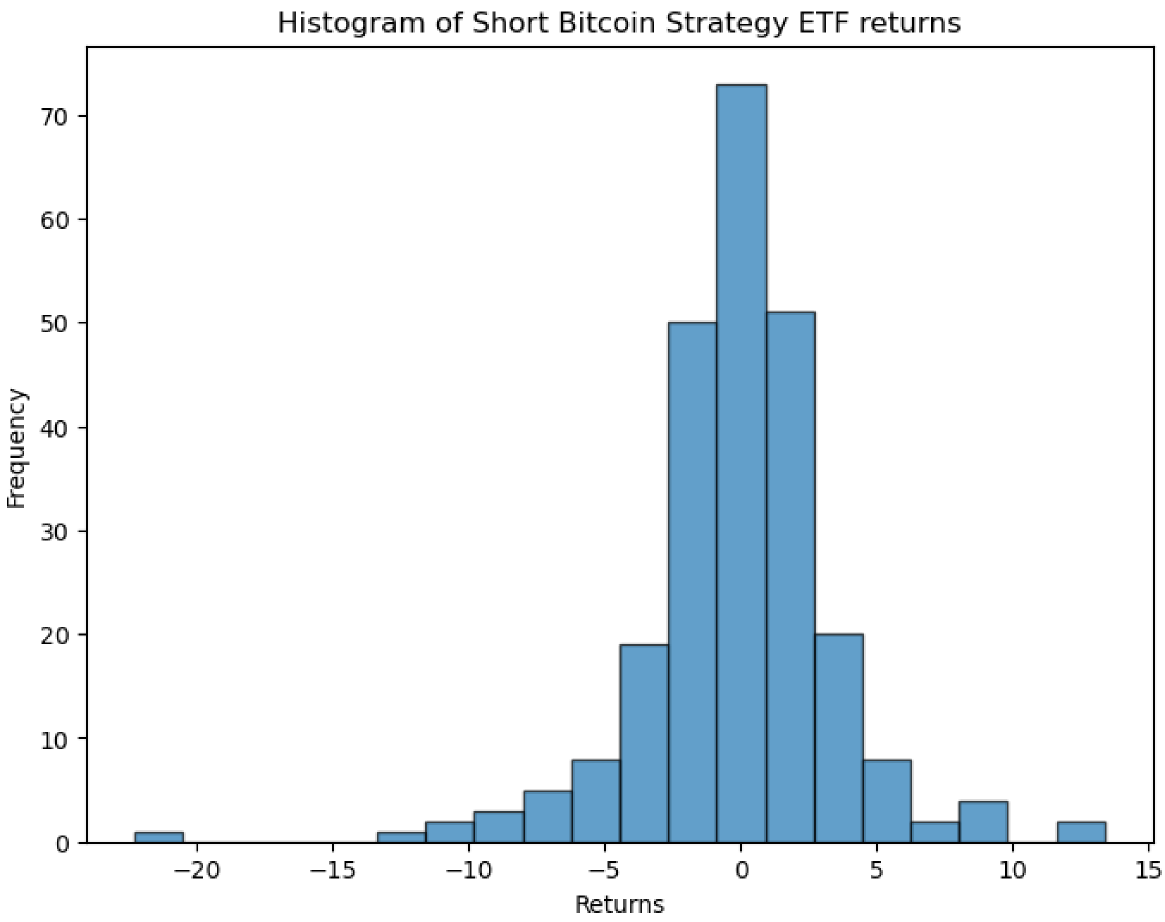
In [23]:

```
print("Average Return:", av_returns_bitcoin)
print("Standard Deviation:", st_deviation_bitcoin)
print("Skewness:", skewness_bitcoin)
print("Kurtosis:", kurtosis_bitcoin)
```

```
Average Return: -0.188
Standard Deviation: 3.715
Skewness: -0.698
Kurtosis: 6.302
```

In [24]:

```
plt.figure(figsize=(8, 6))
plt.hist(data_bitcoinETF['Return'].dropna(), bins=20, edgecolor='black', alpha=0.7
plt.xlabel('Returns')
plt.ylabel('Frequency')
plt.title('Histogram of Short Bitcoin Strategy ETF returns')
plt.show()
```



This is exactly the opposite of the Equity ETF we started with - from the 3rd and 4th moment we can see that the returns were left skewed (skewness<0) and with fat tails (i.e. leptokurtic since kurtosis > 3). These characteristics are not very promising - they imply:

- **left skewness** - higher probability of substantial negative return
- **fat tails** - more risk of extreme events (black swan)

It is not surprising given the one year return of **-64%**

In [25]:
```
year_return_bitcoin = np.log(data_bitcoinETF['Close'][-1]/data_bitcoinETF['Close']
```

In [26]:
```
"{:.0%}".format(year_return_bitcoin)
```

Out[26]:
```
'-64%'
```

Step 2

1. Shorting

a.

The portfolio can be sold short because ETFs are exchanged traded. The beauty of the the instruments we chose is that this is not needed because we can create short leg of equity index and bitcoin by just buying Short ETF that are inverse trackers of the performence of the underlying

b.

Assuming we want to sell short the bond ETF, we can borrow the ETF shares and sell them at the exchange where the ETF is traded. To close the position we buy back the shares and return them to the lending counterparty (usually the broker).

2. Credit Risk

The portfolio has credit risk because the issuer of the ETFs can go bankrupt and default on its obligations. Also the underlying of the ETF can be carry credit risk - in the case of the treasuries ETF there is a risk of US defaulting or downgrade.

3. Portfolio Statistics

a.

We assume equally weighted portfolio of 3 instruments

In [27]:
```
(1/3)*year_return_shortequity+(1/3)*year_return_bond+(1/3)*year_return_bitcoin
```

Out[27]:
```
-0.2798119319752159
```

The portfolio lost 27% in one year!

b.

To commpute the variance we need the covariance between the three instruments.

In [28]:
```
weights = np.array([1/3,1/3,1/3])
```

In [29]:
```
portfolio_df = pd.DataFrame({
    'Equity ETF': data_equityIndex['Return'],
    'Bond ETF': data_bondETF['Return'],
    'Bitcoin ETF': data_bitcoinETF['Return']
})

portfolio_df = portfolio_df.dropna()
```

In [30]:
```
portfolio_df.head(3)
```

Out[30]:

Date	Equity ETF	Bond ETF	Bitcoin ETF
2022-07-26	-0.068417	-0.048316	4.469419
2022-07-27	-0.585726	0.157096	-9.370078
2022-07-28	-1.331397	0.217182	-4.430926

In [31]:
```
st_dev_vector = [st_deviation_equity,st_deviation_bond,st_deviation_bitcoin]
```

In [32]:
```
st_dev_vector
```

Out[32]:
```
[1.201, 0.186, 3.715]
```

In [33]:
```
stdev_mat = np.array([[1.201, 0, 0],
                      [0, 0.002, 0],
                      [0, 0, 3.715]])
```

In [34]:
```
def cov_mat(df):
    rows = len(df.axes[0])
    cols = len(df.axes[1])
    covariance = np.zeros((cols, cols))
    mean = np.mean(df, axis=0)
    for i in range(cols):
        for j in range(cols):
            covariance[i,j] += np.sum((df.iloc[:, i] - mean[i]) * (df.iloc[:, j] -

    return covariance/rows
```

In [35]:
```
cov_mat(portfolio_df)
```

Out[35]:
```
array([[ 1.45020666, -0.01422521,  0.96826982],
       [-0.01422521,  0.03393729, -0.16961559],
       [ 0.96826982, -0.16961559, 13.57396742]])
```

Or easier with the library (there will be some rounding differences)

In [36]:
```
portfolio_df.cov()
```

Out[36]:

	Equity ETF	Bond ETF	Bitcoin ETF
Equity ETF	1.456199	-0.014284	0.972271
Bond ETF	-0.014284	0.034078	-0.170316
Bitcoin ETF	0.972271	-0.170316	13.630058

In [37]:
```
def compute_portfolio_performance(ret_df, weights):
    portfolio_returns = (ret_df * weights).sum(axis=1)
    portfolio_variance = np.dot(weights.T, np.dot(ret_df.cov(), weights))

    return portfolio_returns, portfolio_variance
```

In [38]:
```
weights = np.array([1/3,1/3,1/3])

# Compute portfolio returns and standard deviation
portfolio_returns, portfolio_variance_ = compute_portfolio_performance(portfolio_d
portfolio_st_deviation = portfolio_variance_ ** 0.5
print("\033[1m1-year % Return:\033[0m", sum(portfolio_returns))
print("\033[1mPortfolio Variance:\033[0m", portfolio_variance_)
print("\033[1mPortfolio St.Deviation:\033[0m", portfolio_st_deviation)
```

```
1-year % Return: -25.654002915304716
Portfolio Variance: 1.8550750979907844
Portfolio St.Deviation: 1.362011416248331
```

4. Diversification

a.

Diversification is when we combine several assets which are uncorrelated (or even negatively corrected) so that negative return of one the portfolio constituents is compensated by positive return of another constituent, i.e. risk is diminished because underperforming assets have less influence on the portfolio return.

b.

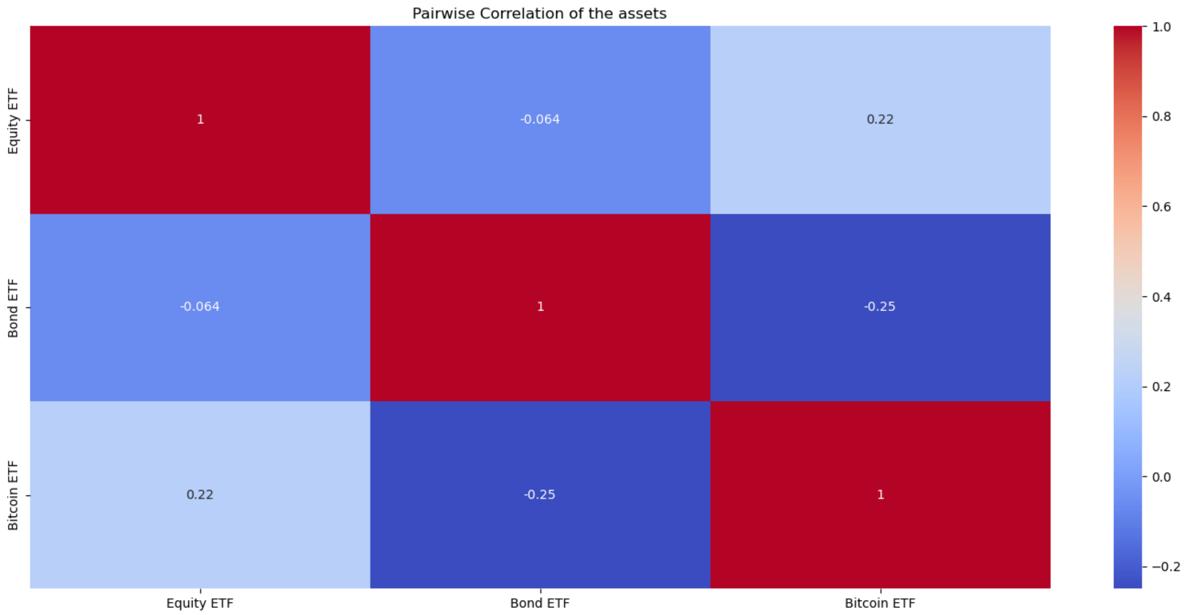
The portfolio we suggest here is well diversified despite the fact that combines two very risky ETFs (short equity and short bitcoin). This can be seen by plotting the correlations between the assets. The treasury (bond) ETF is negatively correlated to bitcoin and equity whereas the correlation between short equities ETF and bitcoin ETF is relatively low.

Moreover we include 3 ETFs and each of them itself combines several underlyings (i.e. this is portfolio of portfolios)

In [39]:
```
corr_matrix = portfolio_df.corr()
```

In [40]:
```
import seaborn as sns
plt.figure(figsize=(18, 8))
sns.heatmap(corr_matrix, annot=True, cmap='coolwarm')

plt.title('Pairwise Correlation of the assets')
plt.show()
```



5. Comparing Portfolios

Portfolio	Return (%)	Volatility (%)
A	-26.48	3.2
B	2.48	0.47
C	-28	1.36

- a. Portfolio C has negative return over the 1-year holding period. Admittedly, it doesn't look very appealing. The main reason for the underperfomance is the spectacular rally of bitcoin since the beginning of 2023. With short bitcoin main driver of the performance it is similar to Portfolio A which is also short bitcoin.
- b. However, it is less risky than A and for risk-free return of say 4%. Now we can observe something very interesting. Everybody knows that high Sharpe ratio is good. This is not always true for negative returns. Portfolio A has higher Sharpe ratio than C

but for much higher volatility. Even though it is slightly less negative, I would prefer portfolio C.

In [41]:
```
#Sharpe ratio - portfolio C
(-0.28-0.04)/1.36
```

Out[41]:
```
-0.23529411764705882
```

In [ ]:
```

```

In [42]:
```
#Sharpe ratio - portfolio A
(-0.26-0.04)/3.2
```

Out[42]:
```
-0.09374999999999999
```

6. Assessing Risk

a.

- One particular scenario in which this portfolio will underperform is if the central banks lose credibility. For instance, energy prices spike again due to supply issues (war in Ukraine induced sanctions on Russia, OPEC supply cuts) and higher energy prices bring more inflation. However, if the central banks around the world (and in particular Fed) decide to stimulate the economy (QE, interest rate cuts, government stimulus programs). This bullish scenario for both equities and bitcoin. FI assets would also profit from loose monetary policy, yet the effect would be likely less pronounced as short-term bonds are more suitable for risk-off scenario.
- Soft landing or scenario where inflation goes back below 2% while economy doesn't fall into recession would send risk-on signal to the equity market. Bitcoin would also profit as it is considered risky asset and the biggest gains occured historically when risk appetite was high.

b.

Loose monetary policy or soft landing would affect also portfolio A (short bitcoin and long bond) though to lesser extent because it doesn't have exposure to equities.

7. Performance

a.

- Risk-off scenario is perfect for our portfolio. First of all, equities and bitcoin will sell off. Secondly, in risk-off environment investors tend to buy short-term bonds (treasuries). Our portfolio will profit on each leg.
- Government crackdown on bitcoin and bitcoin related companies/funds (Binance, Coinbase) will be negative for the crypto world. Our short bitcoin ETF will thrive in such ambience. Increase regulation towards bitcoin is another negative factor that will increase demand for Short Bitcoin Strategy ETF.

b.

Again, these scenarios are favorable for portfolio A because it has long bond and short bitcoin exposure

8. Disrupters

a.

- Dovish central banks that discontinue monetary tightening - increasing the assets balance of Fed or rate cuts that can fuel liquidity and create more inflation in the economy. This can aggravate assets bubbles and our Short Equity ETF will be negatively affected. Furthermore, loose monetary policy will turn investors away from fiat currencies and will push them into buying bitcoin which would be negative for our short bitcoin ETF.
- More regulation from central banks towards crypto money will be beneficial for us because it will affect negatively bitcoin.

b.

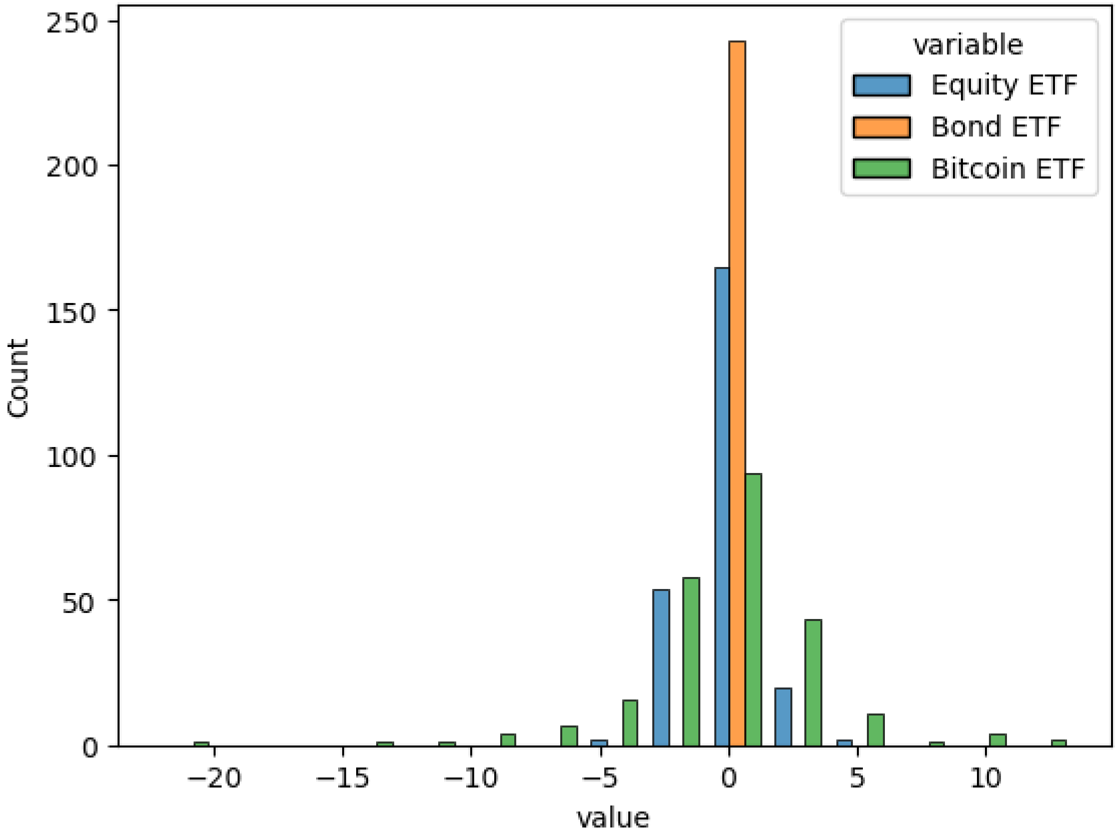
Potential influence from the investment banks can occur if they aggresively allocate to equities or increse their earnings outlook/GDP forecasts, which can term at least in short-term optimism about the economy. In addition, creating products with crypto related underlying can signal recognition by the 'smart money' and increse bitcoin prices. Again, this will mean negative returns of the Short bitcoin ETF in our portfolio.

9. Re-assessing Risk

a.

From the histogram below we can observe that short bitcoin ETF has left skew, whereas bond ETF and equity ETF have very slight right skew.

In [43]:
```
sns.histplot(portfolio_df.melt(), x='value', hue='variable',
             multiple='dodge', shrink=0.75, bins=15);
```

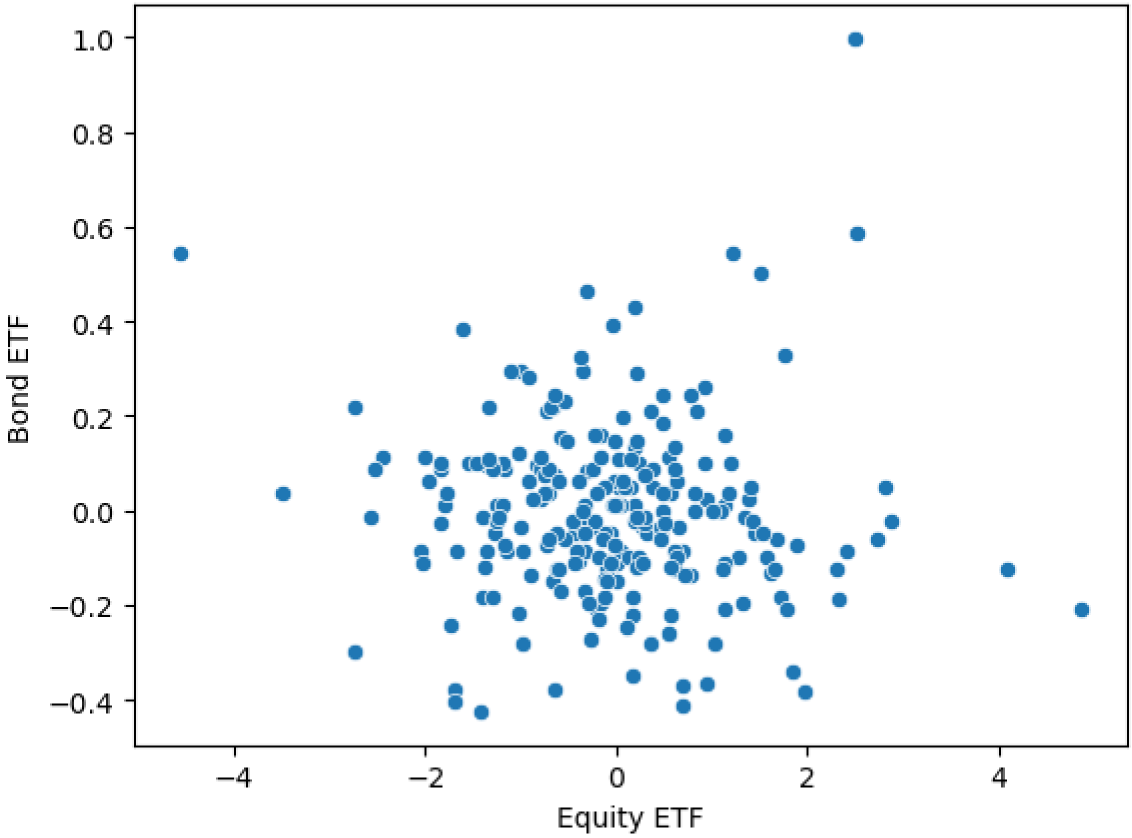


b.

From the plots below it seems that the three assets are uncorellated with the exception of bitcoin and equity appear to be slightly positively correlated. It is not clear whether any non-linear relationship exists.

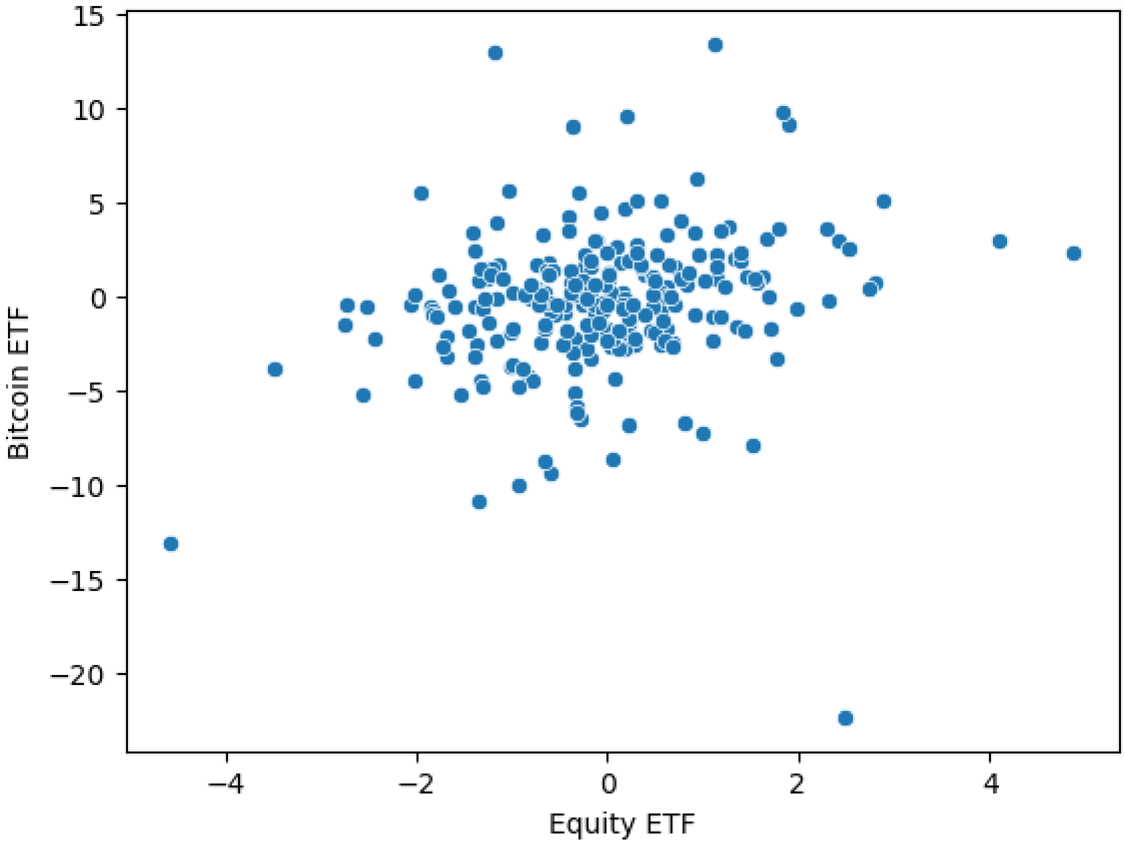
In [44]:
```
sns.scatterplot(x=portfolio_df['Equity ETF'],y=portfolio_df['Bond ETF'])
```

Out[44]:
```
<Axes: xlabel='Equity ETF', ylabel='Bond ETF'>
```



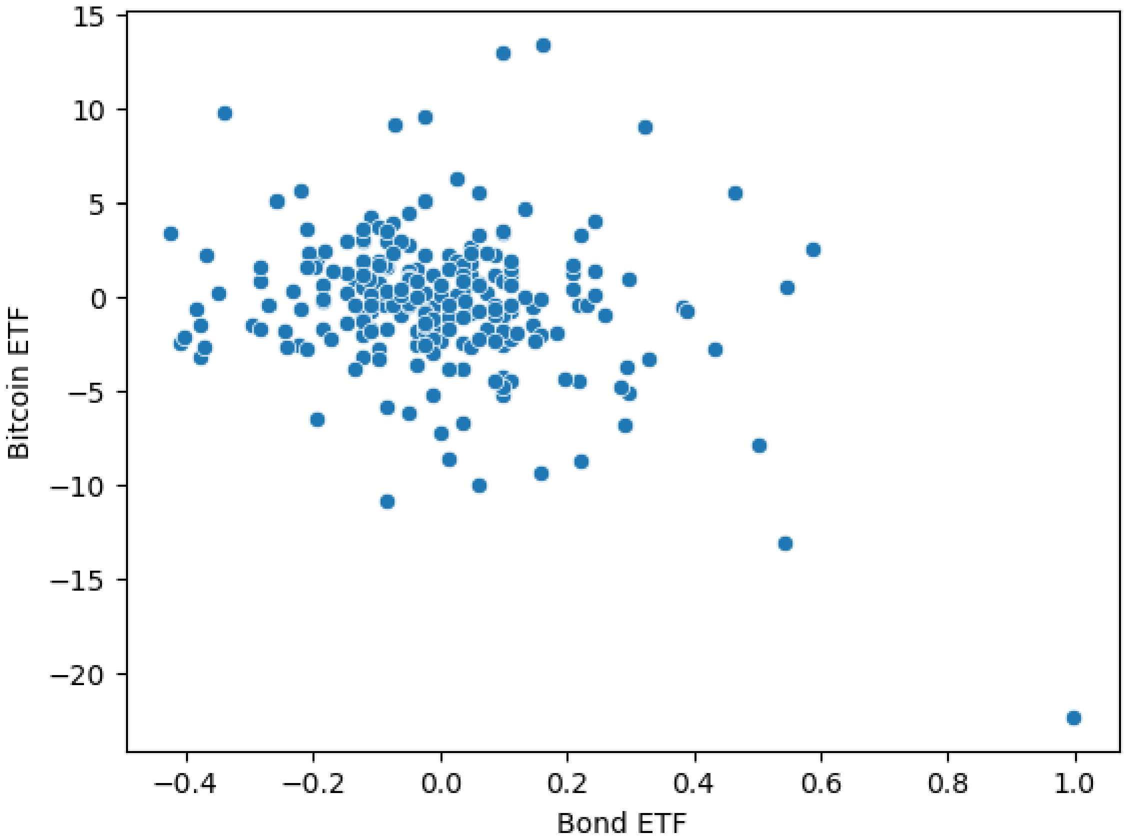
In [45]:
```
sns.scatterplot(x=portfolio_df['Equity ETF'],y=portfolio_df['Bitcoin ETF'])
```

Out[45]: <Axes: xlabel='Equity ETF', ylabel='Bitcoin ETF'>



In [46]:
```
sns.scatterplot(x=portfolio_df['Bond ETF'],y=portfolio_df['Bitcoin ETF'])
```

Out[46]: <Axes: xlabel='Bond ETF', ylabel='Bitcoin ETF'>



Step 4

After careful consideration of all factors affecting the three portfolios and the observed returns and volatilites over 1-year long period we have unanimously concluded that the most robust portfolio is portfolio B.

Portfolio	Return (%)	Volatility (%)	Sharpe Ratio
A	-26.48	3.2	-8.9
B	2.48	0.47	1.02
C	-28.00	1.36	-22.05

We have computed sharpe ratios for all portfolios and not surprisingly B is the best choice. Portfolio A and C have substantial drawdown due to the short leg in bitcoin. In general, over the last year it appears that shorting is too risky. We don't know whether this investor mindset of buying the dip will continue but in any case we don't want to speculate neither on mean reversion (equities and bitcoin correcting) nor on momentum (i.e. the rally to continue). Therefore we suggest portfolio B despite being less diversified (investing in one ETF and one single income stock).

Overall, all team members were on the defensive side. This is why we all included some exposure to fixed income. More aggresive approach would be shorting equities and bitcoin in expectation of risk-off mode. This has not played out well during last months and timing reversal appears next to impossible. Nevertheless, we prefer to stay on the safe side rather than increase exposure to risky assets.

We have chosen Deutsche telekom (DT) since it is the largest telecommunication company in Europe and delivers steady dividends with payout dividend ratio of 40-60% of EPS. Furthermore, the income is relatively secure, with the demand for internet, mobile phones, television and IT services being solid regardless of macro environment. Not only that, we expect the demand to increase with the widespread utilization of AI and data centers. DT is a large cap company and is one of the biggest by market cap in DAX (with large cap historically being safer especially during downturn in economy)

We have included in the portfolio also ETF of investment grade bonds. These bonds being often secured, more liquid and with high credit rating bear less risk during economic downturn. We prefer them also because some institutional investors might be prohibited from investing in high-yield bonds (which would reduce our investor target group). Investing in ETF is also additional diversifier as it includes several issuers.

This portfolio is not without risk. The biggest appears to be inflation spiking up again. This will require further interest rate hikes and with duration risk being high for fixed income, our portfolio will be negatively affected. DT is also very indebted company due to past acquisitions (like T-mobile in USA), hence with higher interest rates will also the payment of interest increase which would ultimately lower the profit of share.

The portfolio targets rather conservative investors (eg. pension funds or insurers). It is certainly for risk-averse investors but at the same time seeking inflation hedge. It will likely provide better returns than money market funds or funds investing solely in government bonds. At the same time it is not exposed to bitcoin which can have extreme volatility.

Last but not least, even if not dare short equities or bitcoin, we believe that risky assets will move at best sideways. Thus including high divident payout stock and invesment grade bond paying coupons is beyond question a good alternative in times of elevated geopolitical and macro risks.