# notebook

January 5, 2022

# 1 Should your fund invest in Bitcoin?

#### 1.1 Background

You work as an analyst at an investment fund in New York. Your CFO wants to explore if it is a good idea to invest some of the fund's assets in Bitcoin. You have to prepare a report on this asset and how it compares to the stock market in general.

# 2 Should your fund invest in Bitcoin?

#### 2.1 Background

You work as an analyst at an investment fund in New York. Your CFO wants to explore if it is a good idea to invest some of the fund's assets in Bitcoin. You have to prepare a report on this asset and how it compares to the stock market in general.

#### 2.2 The data

You have access to three files:

#### Bitcoin daily data in US dollars

- "date" date from September 17, 2014 to November 17, 2021
- "open" the price at the beginning of the trading day
- "high" the highest price reached that day
- "low" the lowest price reached that day
- "close" the price at the closing of the trading day
- "volume" how many Bitcoin were traded that day

#### S&P 500 daily data

- "date" date from September 17, 2014 to November 17, 2021
- "open" the index level at the beginning of the trading day
- "high" the highest level reached that day
- "low" the lowest level reached that day
- "close" the level at the closing of the trading day
- "volume" how many shares in the companies that make up the index were traded that day

#### inflation and gold as monthly data

- "date" date from September, 2014 to November, 2021
- "gold\_usd" price in usd of gold for that month
- "cpi us" the inflation index for the US for that month (cpi = consumer price index)

CPI data from the U.S. Bureau of Labor Statistics. Publicly available information.

Exploratory analysis

2014-09-17 00:00:00 2014-09-01 00:00:00

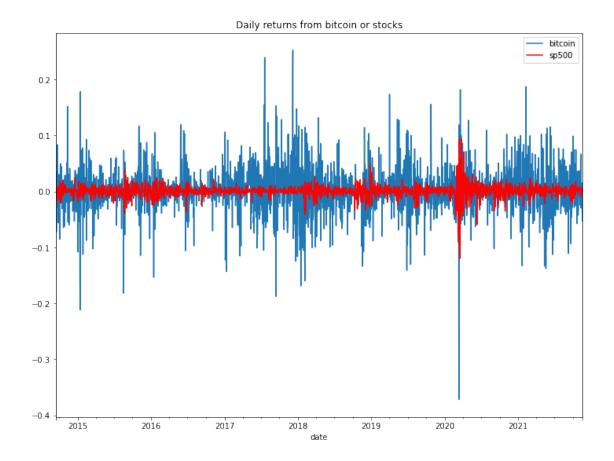
```
[3]: import pandas as pd
    monthly_data = pd.read_csv('./data/monthly_data.csv', parse_dates=['date'])
    monthly_data.head()
[3]:
            date gold_usd
                             cpi_us
    0 2014-09-01 1241.330
                            237.852
    1 2014-10-01 1223.565
                            238.031
    2 2014-11-01 1176.413
                            237.433
    3 2014-12-01 1200.440
                            236.151
    4 2015-01-01 1249.333 234.812
[]: #Assume we bought bitcoin on a particular date and then we compute performance
    sp500 = pd.read_csv('./data/sp500.csv', parse_dates=['date'])
    bitcoin = pd.read_csv('./data/bitcoin-usd.csv', parse_dates=['date'])
    bitcoin.head()
[]:
            date
                        open
                                    high
                                                 low
                                                           close
                                                                      volume
    0 2014-09-17 465.864014 468.174011
                                          452.421997
                                                      457.334015 21056800.0
    1 2014-09-18 456.859985 456.859985
                                          413.104004
                                                      424.440002 34483200.0
    2 2014-09-19 424.102997 427.834991
                                          384.532013
                                                      394.795990
                                                                  37919700.0
    3 2014-09-20 394.673004 423.295990
                                          389.882996 408.903992
                                                                  36863600.0
    4 2014-09-21 408.084991 412.425995
                                          393.181000
                                                      398.821014 26580100.0
[]: print(sp500.date.min())
    print(bitcoin.date.min())
    print(monthly_data.date.min())
    print(bitcoin.shape)
    print(sp500.shape)
    print(monthly_data.shape)
    print(bitcoin.describe())
    print(sp500.describe())
    print(monthly_data.describe())
    2014-09-17 00:00:00
```

```
(2619, 6)
(1805, 6)
(87, 3)
                             high
                                                         close
                                                                       volume
               open
                                             low
                      2615.000000
count
        2615.000000
                                     2615.000000
                                                   2615.000000 2.615000e+03
                     10334.482966
mean
       10051.643066
                                     9750.736512 10073.814423 1.400155e+10
std
       14892.430109
                     15326.320248
                                   14422.269302
                                                 14923.069664 1.993158e+10
min
         176.897003
                       211.731003
                                      171.509995
                                                    178.102997 5.914570e+06
25%
         582.071015
                       588.960998
                                      575.311981
                                                    582.555999 7.489110e+07
50%
        5745.599121
                      5865.881836
                                     5544.089844
                                                   5750.799805 4.679500e+09
75%
        9866.986328
                     10136.996094
                                     9642.615235
                                                   9870.199219
                                                                2.287606e+10
max
       67549.734375
                     68789.625000
                                   66382.062500
                                                  67566.828125
                                                                3.509679e+11
              open
                           high
                                          low
                                                     close
                                                                   volume
count
       1805.000000
                    1805.000000
                                 1805.000000
                                               1805.000000
                                                            1.805000e+03
mean
       2755.938758
                    2769.524277
                                  2741.245103
                                               2756.455533
                                                            3.844502e+09
std
        698.212835
                     701.268104
                                  695.674679
                                                698.850564
                                                            9.781460e+08
       1833.400024
                    1847.000000
                                 1810.099976
                                              1829.079956
                                                            1.296540e+09
min
25%
                    2129.870117
                                 2114.719971
       2123.159912
                                               2124.290039
                                                            3.254950e+09
50%
       2664.439941
                    2682.860107
                                                            3.623320e+09
                                 2648.870117
                                               2663.989990
75%
       3045.750000
                    3068.669922
                                 3012.590088
                                               3039.419922
                                                            4.154240e+09
                                               4701.700195 9.878040e+09
max
       4707.250000
                    4718.500000
                                 4694.390137
          gold usd
                        cpi us
count
         87.000000
                     87.000000
mean
       1403.186678
                    249.790759
        257.985374
                     10.733951
std
       1068.317000
                    233.707000
min
25%
       1231.081500
                    240.428500
50%
       1283.189000
                    249.554000
75%
       1577.216000
                    257.091000
max
       2041.700000
                    276.589000
```

Bitcoin versus stock volatility

If we analyse daily returns of bitcoin versus stock market we find bitcoin is very volatile

[]: <matplotlib.legend.Legend at 0x7f63a3a9c430>



Understanding volatilty monthly for gold bitcoin and sp500

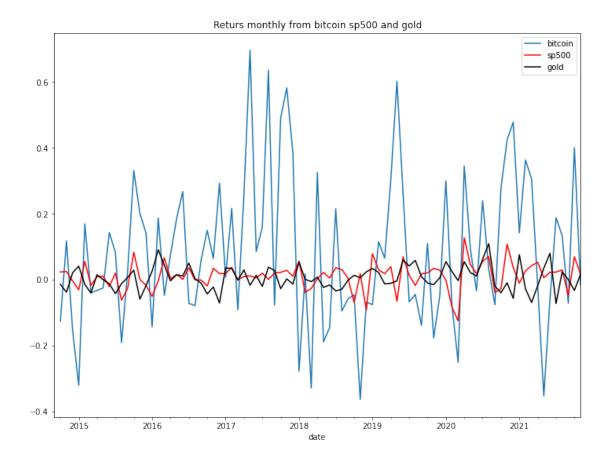
```
import matplotlib.pyplot as plt

monthly_bitcoin_returns=bitcoin['close'].resample('M').ffill().pct_change()
ax1=monthly_bitcoin_returns.plot(figsize=(12,9))

monthly_sp500_returns=sp500.close.resample('M').ffill().pct_change()
monthly_sp500_returns.plot(figsize=(12,9),color='red')
monthly_data['returns_gold']=monthly_data.gold_usd.pct_change(1)

monthly_data.set_index(monthly_data.date,inplace=True)
monthly_data['returns_gold'].plot(figsize=(12,9),color='black')
ax1.legend(['bitcoin','sp500','gold'])
ax1.set_title('Returs monthly from bitcoin sp500 and gold')
```

[]: Text(0.5, 1.0, 'Returs monthly from bitcoin sp500 and gold')

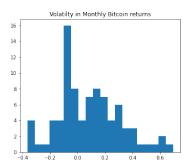


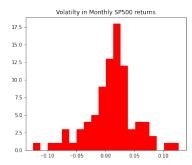
From the graph we can see that bitcoin is the most volatile with returns on a monthly basis changing close to 5-6%

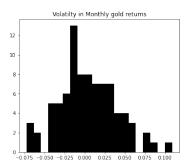
The below histogram helps to quantify the spread of the returns

```
fig, axs = plt.subplots(nrows=1,ncols=3,figsize=(20,5))
axs[0].hist(monthly_bitcoin_returns,bins=20)
axs[0].set_title('Volatilty in Monthly Bitcoin returns')
axs[1].hist(monthly_sp500_returns,color='red',bins=20)
axs[1].set_title('Volatilty in Monthly SP500 returns')
axs[2].hist(monthly_data.returns_gold,color='black',bins=20)
axs[2].set_title('Volatilty in Monthly gold returns')
```

[]: Text(0.5, 1.0, 'Volatilty in Monthly gold returns')





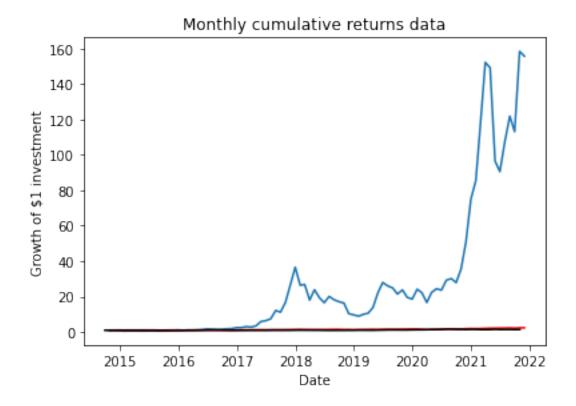


#### PERFORMANCE OF BITCOIN VERSUS STOCK VERSUS GOLD

```
[]: fig = plt.figure()
    ax1 = fig.add_axes([0.1,0.1,0.8,0.8])
    #bitcoin_cum_returns = (bitcoin.returns+ 1).cumprod()

monthly_cum_returns = (monthly_bitcoin_returns + 1).cumprod()
    monthly_sp500_cum_returns = (monthly_sp500_returns+ 1).cumprod()
    monthly_data_cum_returns = (monthly_data.returns_gold+ 1).cumprod()

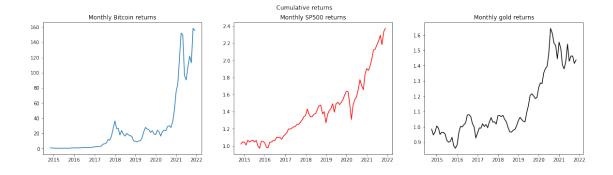
ax1.plot(monthly_cum_returns)
    ax1.plot(monthly_sp500_cum_returns,color='red')
    ax1.plot(monthly_data_cum_returns,color='black')
    ax1.set_xlabel("Date")
    ax1.set_ylabel("Growth of $1 investment")
    ax1.set_title("Monthly cumulative returns data")
    plt.show()
```



```
fig, axs = plt.subplots(nrows=1,ncols=3,figsize=(20,5))

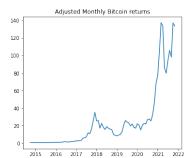
fig.suptitle('Cumulative returns')
axs[0].plot(monthly_cum_returns)
axs[0].set_title('Monthly Bitcoin returns')
axs[1].plot(monthly_sp500_cum_returns,color='red')
axs[1].set_title('Monthly SP500 returns')
axs[2].plot(monthly_data_cum_returns,color='black')
axs[2].set_title('Monthly gold returns')
```

### []: Text(0.5, 1.0, 'Monthly gold returns')



```
[]: | idx=pd.DatetimeIndex(monthly_cum_returns.index.year.
     ⇒astype(str)+'-'+monthly_cum_returns.index.month.astype('str'))
     bitcoin_df=pd.DataFrame(monthly_cum_returns).set_index(idx)
     idx1=pd.DatetimeIndex(monthly_sp500_cum_returns.index.year.
     →astype(str)+'-'+monthly_sp500_cum_returns.index.month.astype(str))
     sp500_df=pd.DataFrame(monthly_sp500_cum_returns).set_index(idx1)
     idx2=pd.DatetimeIndex(monthly_data_cum_returns.index.year.
      →astype(str)+'-'+monthly_data_cum_returns.index.month.astype(str))
     gold df=pd.DataFrame(monthly data cum returns).set index(idx2)
     df1=gold_df.merge(bitcoin_df,left_index=True,right_index=True)
     df1.columns=['gold_returns', 'bitcoin_returns']
     df2=df1.merge(monthly_data,left_index=True,right_index=True)
     reqd_df=df2[['gold_returns','bitcoin_returns','cpi_us']]
     reqd_df=reqd_df.merge(sp500_df,left_index=True,right_index=True)
     reqd_df.columns=['gold_returns','bitcoin_returns','cpi_us','sp500_returns']
     reqd_df['base_cpi']=reqd_df.cpi_us[0]
     reqd_df['adj_gold']=reqd_df.gold_returns*reqd_df.base_cpi/reqd_df.cpi_us
     reqd_df['adj_bitcoin']=reqd_df.bitcoin_returns*reqd_df.base_cpi/reqd_df.cpi_us
     reqd_df['adj_stock']=reqd_df.sp500_returns*reqd_df.base_cpi/reqd_df.cpi_us
     adj bitcoin df=reqd df['adj bitcoin']
     adj_gold_df=reqd_df['adj_gold']
     adj_stock_df=reqd_df['adj_stock']
     fig, axs = plt.subplots(nrows=1,ncols=3,figsize=(20,5))
     axs[0].plot(adj_bitcoin_df)
     axs[0].set_title('Adjusted Monthly Bitcoin returns')
     axs[1].plot(adj_gold_df)
     axs[1].set_title('Adjusted Monthly Gold returns')
     axs[2].plot(adj stock df)
     axs[2].set_title('Adjusted Monthly Stock returns')
```

[]: Text(0.5, 1.0, 'Adjusted Monthly Stock returns')







Bitcoin has a good growth but is much more volatile than both stocks and gold. After inflation adjusting we observe the returns are still good for bitcoin. For every 1\$ invested we get 140\$ in 2022. Depending on the expected return and risk profile investing in bitcoin may be to a good hedge against inflation

### Portfolio expectaions

Since we are looking to lower our volatility we want to limit exposure to bitcoin. Depending on our risk appetite a maximum of 10-15% of asset allocation would be ideal. Stocks have higher returns than gold but they are also more volative .So I would suggest 70-75% exposure to stocks and the rest I would invest in gold 15-20%.

## 2.3 Competition challenge

Create a report that covers the following:

- 1. How does the performance of Bitcoin compare to the S&P 500 and the price of gold?
- 2. Analyze Bitcoin's returns and volatility profile. Do you believe it could help improve the performance of a portfolio? Do you believe Bitcoin could be used as a hedge versus inflation?
- 3. The CFO is looking to lower volatility in the fund. Explore building a portfolio using some or all of these assets. Make a recommendation that minimizes overall risk.

[]:

## 2.4 Judging criteria

CATEGORY WEIGHTING DETAILS

#### | Recommendations | 35% |

Clarity of recommendations - how clear and well presented the recommendation is.

Quality of recommendations - are appropriate analytical techniques used & are the conclusions valid?

Number of relevant insights found for the target audience.

1

### | Storytelling | 30% |

How well the data and insights are connected to the recommendation.

How the narrative and whole report connects together.

Balancing making the report in depth enough but also concise.

```
| | Visualizations | 25% |
```

Appropriateness of visualization used.

Clarity of insight from visualization.

```
| | Votes | 10% |
```

Up voting - most upvoted entries get the most points.

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# 2.5 Checklist before publishing into the competition

- Rename your workspace to make it descriptive of your work. N.B. you should leave the notebook name as notebook.ipynb.
- Remove redundant cells like the judging criteria so the workbook is focused on your story.
- Make sure the workbook reads well and explains how you found your insights.
- Check that all the cells run without error.

## 2.6 Time is ticking. Good luck!

[]: