Quantatative Investment Project

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Abstract: In this report, I will demonstrate a quantitative approach by combining momentum and reversal strategy to long the selected stocks with a daily basis and achieve excess return.

Data Set Information: The data is from the WRSD website (https://wrds-www.wharton.upenn.edu). The CRSP U.S. Stock database contains end-of-day and month-end prices on primary listings for the NYSE, NYSE MKT, NASDAQ, and Arca exchanges, along with basic market indices. CRSP databases are characterized by their comprehensive corporate action information and highly accurate total return calculations.

Project Description:

I believe that if a stock price is stable and has neither upside nor downside momentum, the reversal strategy would be most effective because prices would probably go back up to original price levels after some indications of decline in stock price. In the notebook, I will demonstrate the rate of return of our strategy. I use quntile method to classify stocks into groups and select the group according to our strategy above. I use data from 2000 - 2010 to build our strategy and test with 2010-2018 data.

Comments and Explanations (in the form of Markdown) are included in the notebook to improve the readability of the code, to explain the rationale of doing certain steps and to discuss the results and inferences from the executed code.

In [1]:
```
import pandas as pd
import numpy as np
import statsmodels.api as sm
import matplotlib.pyplot as plt
import seaborn as sn
```

In [2]:
```
data = pd.read_feather("data_test.feather")

first_date = '2000-01-01'
last_date  = '2010-12-31'
data = data.loc[(data['DATE']>=first_date) & (data['DATE']<=last_date)]
## I want to apply our method for the 2000-2010. And I will test if it's working for during 2010-2020.

data['MV'] = data['SHROUT'] * np.abs(data['OPENPRC'])
## Our strategy will be computed at the beginning of the days,
## so We apply the Market Value as MV by computing share outstanding * openning price.

data['XRET'] = data['RET']
data = data.drop(['TICKER','OPENPRC','BID','ASK', 'ASKHI', 'BIDLO', 'NUMTRD', 'RET', 'SHROUT'],axis=1)

data = data.sort_values(by = ['PERMNO','DATE'])
data = data.groupby(['PERMNO','DATE']).tail(1)
data.set_index(['PERMNO','DATE'], inplace=True)
data.sort_index(inplace=True)
data
```

Out[2]:

		PRC	VOL	SPRTRN	MV	XRET
PERMNO	**DATE**					
10001.0	**2000-01-03**	8.562500	1721.0	-0.009549	2.067188e+04	0.007353
	2000-01-04	8.437500	1080.0	-0.038345	2.067188e+04	-0.014599
	2000-01-05	8.562500	1711.0	0.001922	2.067188e+04	0.014815
	2000-01-06	8.500000	580.0	0.000956	2.082500e+04	-0.007299
	2000-01-07	8.437500	1406.0	0.027090	2.097812e+04	-0.007353
...	**...**	...	...	...	...	...
93436.0	**2010-12-27**	25.549000	9407934.0	0.000613	2.613453e+06	-0.150914
	2010-12-28	26.410000	4107002.0	0.000771	2.411055e+06	0.033700
	2010-12-29	27.730000	3363184.0	0.001009	2.521115e+06	0.049981
	2010-12-30	26.500000	2063322.0	-0.001508	2.583607e+06	-0.044356
	2010-12-31	26.629999	1429604.0	-0.000191	2.521706e+06	0.004906

19874551 rows × 5 columns

- In the following cell, we will build some variables including momentum index, moving average index and information discreteness index. We will use quntile groups based on these index to illustrate our strategy.

In [3]:

In [3]:
```
data['LAG_VOL'] = data.groupby('PERMNO')['VOL'].shift()
## Volume Lag for screening.
## We are aiming at low market value stocks, thus some of these stocks are extremely involatile
## We want to make sure that there are some levels of trading volumes before we apply our strategy


minlag = 22
maxlag = 88
data['CUMGROSSRET'] = (1+data['XRET']).groupby('PERMNO').cumprod()
data['MOMENTUM'] = data['CUMGROSSRET'].groupby('PERMNO').shift(minlag) / data['CUMGROSSRET'].groupby('PERMNO').sh
## We will use the period from 4 month (88 trading days) ago to 1 month (22 trading days) ago to check momentum
## We use the cumulative gross return to get our momentum index.


data['MA'] = data.groupby('PERMNO')['XRET'].rolling(10).mean().shift().reset_index(0,drop = True)
## We use the previous two weeks (10 trading days) moving average to check if the reversal appears.


data['UP'] = 0
data['UP'].loc[data['XRET'] >= 0] = 1
data['DIFT'] = data.groupby('PERMNO')['UP'].rolling(230).mean().shift(22).reset_index(0,drop = True)
data['ID'] = (1+data['MOMENTUM'])*(1-2*data['DIFT'])
## We apply the formula of information discreteness

data.head(5)
```

```
/Users/sky/opt/anaconda3/lib/python3.9/site-packages/pandas/core/indexing.py:1732: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#retur
ning-a-view-versus-a-copy
  self._setitem_single_block(indexer, value, name)
```

Out[3]:

		PRC	VOL	SPRTRN	MV	XRET	LAG_VOL	CUMGROSSRET	MOMENTUM	MA	UP	DIFT	ID
PERMNO	DATE												
10001.0	2000-01-03	8.5625	1721.0	-0.009549	20671.875	0.007353	NaN	1.007353	NaN	NaN	1	NaN	NaN
	2000-01-04	8.4375	1080.0	-0.038345	20671.875	-0.014599	1721.0	0.992647	NaN	NaN	0	NaN	NaN
	2000-01-05	8.5625	1711.0	0.001922	20671.875	0.014815	1080.0	1.007353	NaN	NaN	1	NaN	NaN
	2000-01-06	8.5000	580.0	0.000956	20825.000	-0.007299	1711.0	1.000000	NaN	NaN	0	NaN	NaN
	2000-01-07	8.4375	1406.0	0.027090	20978.125	-0.007353	580.0	0.992647	NaN	NaN	0	NaN	NaN

In [4]:
```
## To manipulate our data into time sequnce structure, we reset the index order.
data_2 = data.reorder_levels(['DATE','PERMNO'])
data_2.sort_index(inplace=True)
data_2.dropna(inplace=True)
data_2.head()
data_2
```

Out[4]:

		PRC	VOL	SPRTRN	MV	XRET	LAG_VOL	CUMGROSSRET	MOMENTUM	MA	UP	DIFT	
DATE	PERMNO												
2000-12-29	10001.0	9.750000	2104.0	-0.010448	2.404325e+04	0.012987	1600.0	1.215636	0.168806	0.000067	1	0.639130	-0
	10012.0	2.000000	684329.0	-0.010448	4.170331e+04	-0.058824	263678.0	0.249027	-0.568421	-0.047530	0	0.469565	0
	10016.0	22.375000	35455.0	-0.010448	3.954732e+05	-0.040214	16319.0	1.185430	0.190436	0.001246	0	0.534783	-0
	10019.0	3.500000	435839.0	-0.010448	1.964125e+04	0.435897	47793.0	0.347826	-0.138889	-0.002867	1	0.526087	-0
	10025.0	44.687500	18500.0	-0.010448	3.410679e+05	-0.006944	19500.0	1.735437	0.418259	0.000016	0	0.600000	-0
...	...	...	...	...	...	...	...	...	...	...	...	...	
2010-12-31	93192.0	5.670000	30368.0	-0.000191	2.863560e+05	-0.029110	88322.0	0.821739	-0.237437	0.007933	0	0.469565	0
	93193.0	3.790000	95842.0	-0.000191	1.918246e+04	0.035519	44775.0	0.437140	-0.226415	0.007749	1	0.482609	0
	93194.0	8.710000	266417.0	-0.000191	1.294964e+05	0.031991	373906.0	0.034495	-0.511879	0.000937	1	0.391304	0
	93195.0	3.780000	2100.0	-0.000191	5.331750e+04	0.010695	1599.0	0.757515	0.301003	0.001396	1	0.526087	-0
	93223.0	52.060001	151600.0	-0.000191	2.764365e+06	-0.020324	89300.0	1.047856	0.120054	0.002884	0	0.504348	-0

15624615 rows × 12 columns

In [5]:
```
def quintiles(inser):
    outser = pd.qcut(inser, q=5, labels=range(1,6))
    return outser
```

```
data_2['QUINTILE_mv'] = data_2['MV'].groupby('DATE').apply(quintiles)
data_2['QUINTILE_mom'] = data_2['MOMENTUM'].groupby('DATE').apply(quintiles)
data_2['QUINTILE_ma'] = data_2['MA'].groupby('DATE').apply(quintiles)
data_2['QUINTILE_id'] = data_2['ID'].groupby('DATE').apply(quintiles)
data_2

## We use the quintiles approach to divide all our parameters into 5 subgroups.
```

Out[5]:

DATE	PERMNO	PRC	VOL	SPRTRN	MV	XRET	LAG_VOL	CUMGROSSRET	MOMENTUM	MA	UP	DIFT	
2000-12-29	10001.0	9.750000	2104.0	-0.010448	2.404325e+04	0.012987	1600.0	1.215636	0.168806	0.000067	1	0.639130	-0
	10012.0	2.000000	684329.0	-0.010448	4.170331e+04	-0.058824	263678.0	0.249027	-0.568421	-0.047530	0	0.469565	0
	10016.0	22.375000	35455.0	-0.010448	3.954732e+05	-0.040214	16319.0	1.185430	0.190436	0.001246	0	0.534783	-0
	10019.0	3.500000	435839.0	-0.010448	1.964125e+04	0.435897	47793.0	0.347826	-0.138889	-0.002867	1	0.526087	-0
	10025.0	44.687500	18500.0	-0.010448	3.410679e+05	-0.006944	19500.0	1.735437	0.418259	0.000016	0	0.600000	-0
...	...	...	...	...	...	...	...	...	...	...	...	...	
2010-12-31	93192.0	5.670000	30368.0	-0.000191	2.863560e+05	-0.029110	88322.0	0.821739	-0.237437	0.007933	0	0.469565	0
	93193.0	3.790000	95842.0	-0.000191	1.918246e+04	0.035519	44775.0	0.437140	-0.226415	0.007749	1	0.482609	0
	93194.0	8.710000	266417.0	-0.000191	1.294964e+05	0.031991	373906.0	0.034495	-0.511879	0.000937	1	0.391304	0
	93195.0	3.780000	2100.0	-0.000191	5.331750e+04	0.010695	1599.0	0.757515	0.301003	0.001396	1	0.526087	-0
	93223.0	52.060001	151600.0	-0.000191	2.764365e+06	-0.020324	89300.0	1.047856	0.120054	0.002884	0	0.504348	-0

15624615 rows × 16 columns

In [6]:
```
ports = data_2.loc[ (data_2['QUINTILE_ma'] == 1) &
                    (data_2['QUINTILE_mom'] == 3) &
                    (data_2['QUINTILE_mv'] == 1) &
                    (data_2['QUINTILE_id'] == 1) &
                    (data_2['LAG_VOL'] >= 5000), ].groupby('DATE')['XRET'].mean()

ports.mean() ## Average Daily Rate of Return
```

Out[6]:
```
0.010584410965484256
```

In [7]:
```
(ports.mean() / ports.std())  ## Sharpe Ratio
```

Out[7]:
```
0.19205136125934955
```

- Our Result shows an extraordinary return and sharpe ratio for each day. However, in somedays, our strategy doesn't make any trade. Thus, we will take the following steps to change those days to 0 and output an annual return.

In [8]:
```
data_3 = data_2.reset_index(1,drop = True)
df_result = data_3.groupby('DATE')['XRET'].mean()
df_result = df_result.to_frame()
ports_2 = ports.to_frame()

df_result['S&P Ret'] = data.groupby('DATE')['SPRTRN'].mean()
df_result['OUR_RET'] = ports_2['XRET']
df_result['OUR_RET'] = df_result['OUR_RET'].fillna(0)
df_result['OUR_RET'].mean()  ## Avg Return after penalizing for the no-trade days
```

Out[8]:
```
0.009970212236962515
```

In [9]:
```
(df_result['OUR_RET'].mean() / df_result['OUR_RET'].std()) * np.sqrt(250) ## Sharpe Ratio
```

Out[9]:
```
2.944063044793323
```

- Even after we fill no trade days with 0 return, our strategy still shows about 0.58% daily return on average. And have an annual sharpe ratio around 2.5

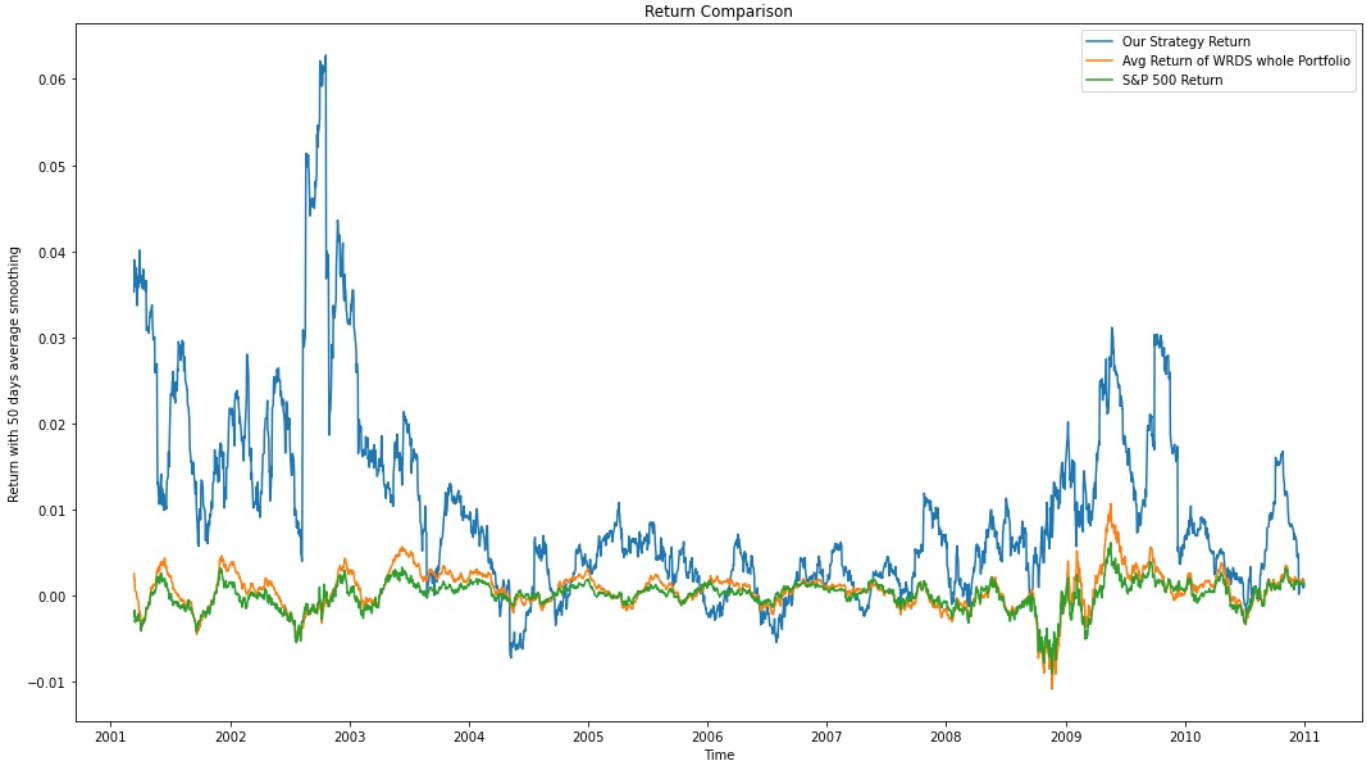
Visualization:

Visualization:

The following plots are some visualizations of our results.

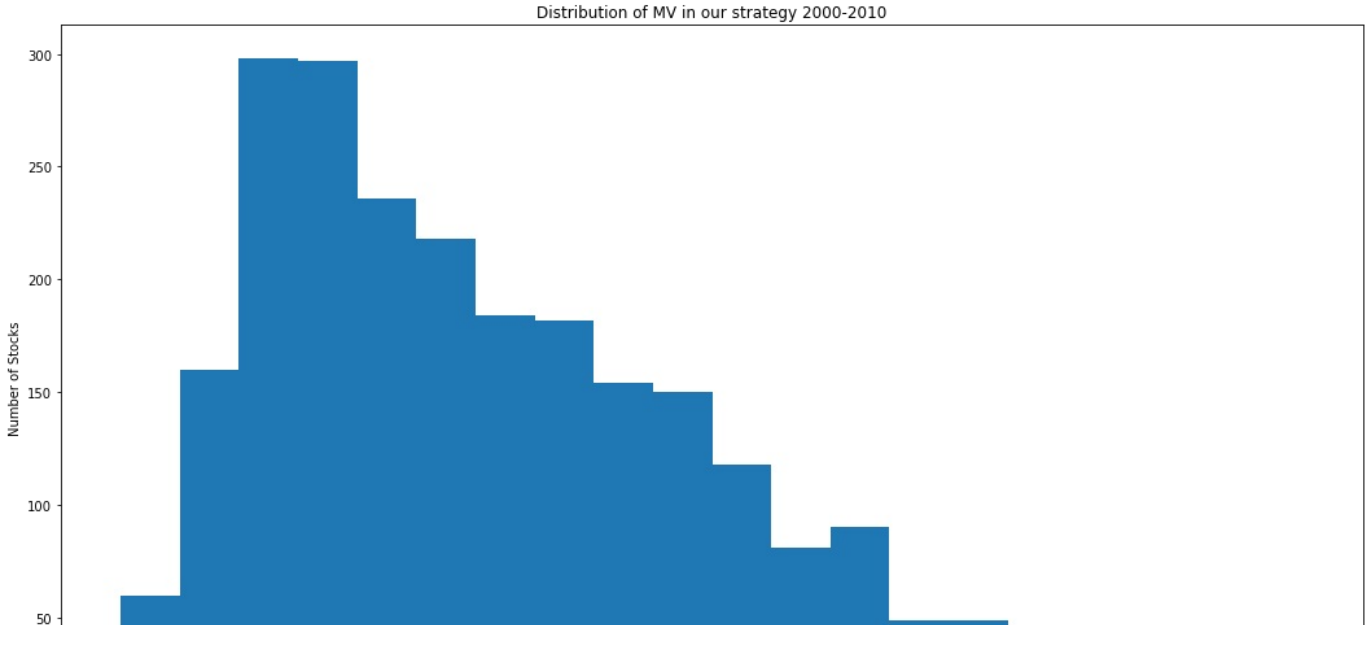
In [10]:

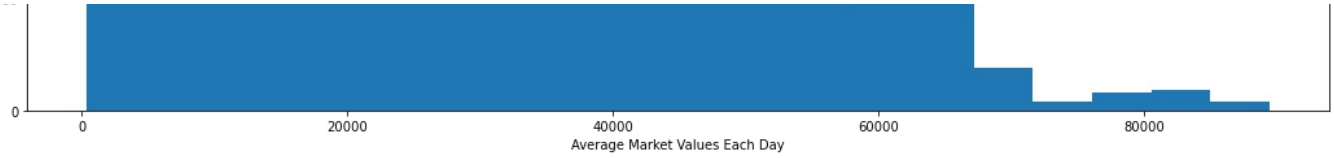
```
plt.figure(figsize=(18,10))
plt.title("Return Comparison")
plt.xlabel('Time')
plt.ylabel('Return with 50 days average smoothing')
plt.plot(df_result['OUR_RET'].rolling(50).mean(), label = "Our Strategy Return")
plt.plot(df_result['XRET'].rolling(50).mean(), label = "Avg Return of WRDS whole Portfolio")
plt.plot(df_result['S&P Ret'].rolling(50).mean(), label = "S&P 500 Return")
plt.legend()
plt.show()
```



In [11]:

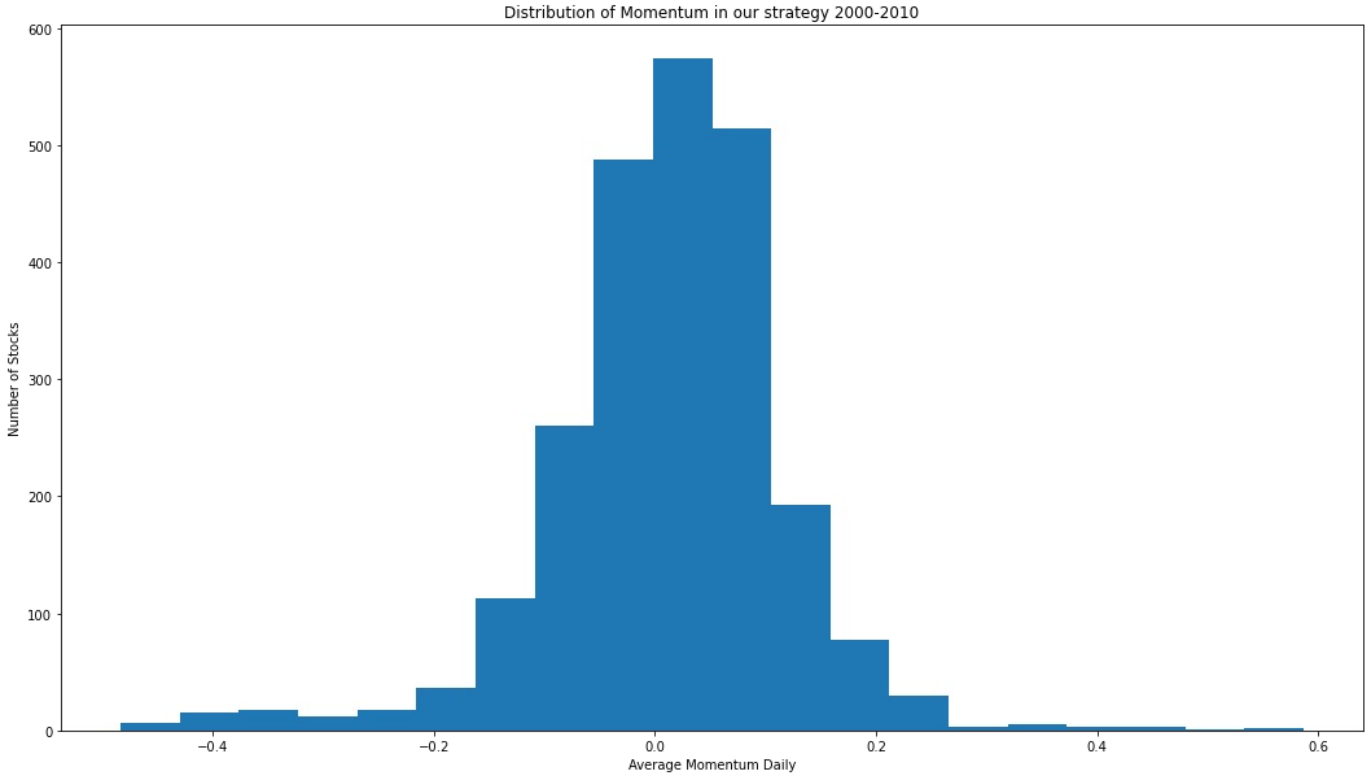
```
df_for_plot = data_2.loc[ (data_2['QUINTILE_ma'] == 1) &
                 (data_2['QUINTILE_mom'] == 3) &
                 (data_2['QUINTILE_mv'] == 1) &
                 (data_2['QUINTILE_id'] == 1) &
                 (data_2['LAG_VOL'] >= 5000), ].groupby('DATE').mean()

plt.figure(figsize=(18,10))
plt.hist(df_for_plot['MV'],bins=20)
plt.title("Distribution of MV in our strategy 2000-2010")
plt.xlabel('Average Market Values Each Day')
plt.ylabel('Number of Stocks')
plt.show()
```





In [12]:

```
plt.figure(figsize=(18,10))
plt.hist(df_for_plot['MOMENTUM'],bins=20)
plt.title("Distribution of Momentum in our strategy 2000-2010")
plt.xlabel('Average Momentum Daily')
plt.ylabel('Number of Stocks')
plt.show()
```



- In the following steps, we will check if our method works for 2010-2020.

In [13]:

```
data = pd.read_feather("data_test.feather")

first_date = '2010-01-01'
last_date  = '2020-12-31'
data = data.loc[(data['DATE']>=first_date) & (data['DATE']<=last_date)]

data['MV'] = data['SHROUT'] * np.abs(data['OPENPRC'])
data['XRET'] = data['RET']
data = data.drop(['TICKER','OPENPRC','BID','ASK', 'ASKHI', 'BIDLO', 'NUMTRD', 'RET', 'SHROUT'],axis=1)

data = data.sort_values(by = ['PERMNO','DATE'])
data = data.groupby(['PERMNO','DATE']).tail(1)
data.set_index(['PERMNO','DATE'], inplace=True)
data.sort_index(inplace=True)

data['LAG_VOL'] = data.groupby('PERMNO')['VOL'].shift()

minlag = 22
maxlag = 88
data['CUMGROSSRET'] = (1+data['XRET']).groupby('PERMNO').cumprod()
data['MOMENTUM'] = data['CUMGROSSRET'].groupby('PERMNO').shift(minlag) / data['CUMGROSSRET'].groupby('PERMNO').sh
data['MA'] = data.groupby('PERMNO')['XRET'].rolling(10).mean().shift().reset_index(0,drop = True)
data['UP'] = 0
data['UP'].loc[data['XRET'] >= 0] = 1
data['DIFT'] = data.groupby('PERMNO')['UP'].rolling(230).mean().shift(22).reset_index(0,drop = True)
data['ID'] = (1+data['MOMENTUM'])*(1-2*data['DIFT'])
data.head(5)
```

```
/Users/sky/opt/anaconda3/lib/python3.9/site-packages/pandas/core/indexing.py:1732: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#retur
```

```
ning-a-view-versus-a-copy
  self._setitem_single_block(indexer, value, name)
```

Out[13]:

		PRC	VOL	SPRTRN	MV	XRET	LAG_VOL	CUMGROSSRET	MOMENTUM	MA	UP	DIFT	ID
PERMNO	DATE												
10001.0	2010-01-04	10.25	18500.0	0.016043	46139.379667	-0.004854	NaN	0.995146	NaN	NaN	0	NaN	NaN
	2010-01-05	10.19	23200.0	0.003116	44394.981331	-0.005854	18500.0	0.989320	NaN	NaN	0	NaN	NaN
	2010-01-06	10.31	18700.0	0.000546	44394.981331	0.011776	23200.0	1.000971	NaN	NaN	1	NaN	NaN
	2010-01-07	9.96	29200.0	0.004001	44831.078835	-0.033948	18700.0	0.966990	NaN	NaN	0	NaN	NaN
	2010-01-08	10.34	25100.0	0.002882	43610.000000	0.038153	29200.0	1.003883	NaN	NaN	1	NaN	NaN

In [14]:
```
## To manipulate our data into time sequnce structure, we reset the index order.
data_2 = data.reorder_levels(['DATE','PERMNO'])
data_2.sort_index(inplace=True)
data_2.dropna(inplace=True)
data_2['QUINTILE_mv'] = data_2['MV'].groupby('DATE').apply(quintiles)
data_2['QUINTILE_mom'] = data_2['MOMENTUM'].groupby('DATE').apply(quintiles)
data_2['QUINTILE_ma'] = data_2['MA'].groupby('DATE').apply(quintiles)
data_2['QUINTILE_id'] = data_2['ID'].groupby('DATE').apply(quintiles)
```

In [15]:
```
ports = data_2.loc[ (data_2['QUINTILE_ma'] == 1) &
                    (data_2['QUINTILE_mom'] == 3) &
                    (data_2['QUINTILE_mv'] == 1) &
                    (data_2['QUINTILE_id'] == 1) &
                    (data_2['LAG_VOL'] >= 5000), ].groupby('DATE')['XRET'].mean()

ports.mean()
```

Out[15]:
```
0.0033885937762923894
```

In [16]:
```
ports.mean() / ports.std()
```

Out[16]:
```
0.11094295958256413
```

In [17]:
```
data_3 = data_2.reset_index(1,drop = True)
df_result = data_3.groupby('DATE')['XRET'].mean()
df_result = df_result.to_frame()
ports_2 = ports.to_frame()

df_result['S&P Ret'] = data.groupby('DATE')['SPRTRN'].mean()
df_result['OUR_RET'] = ports_2['XRET']
df_result['OUR_RET'] = df_result['OUR_RET'].fillna(0)
df_result['OUR_RET'].mean()
```

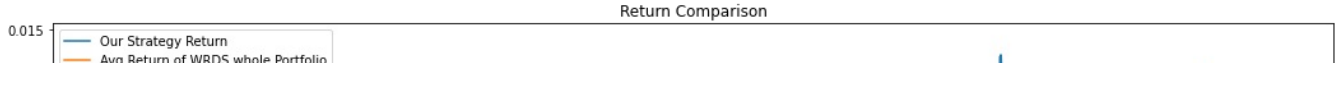
Out[17]:
```
0.002614788604978599
```

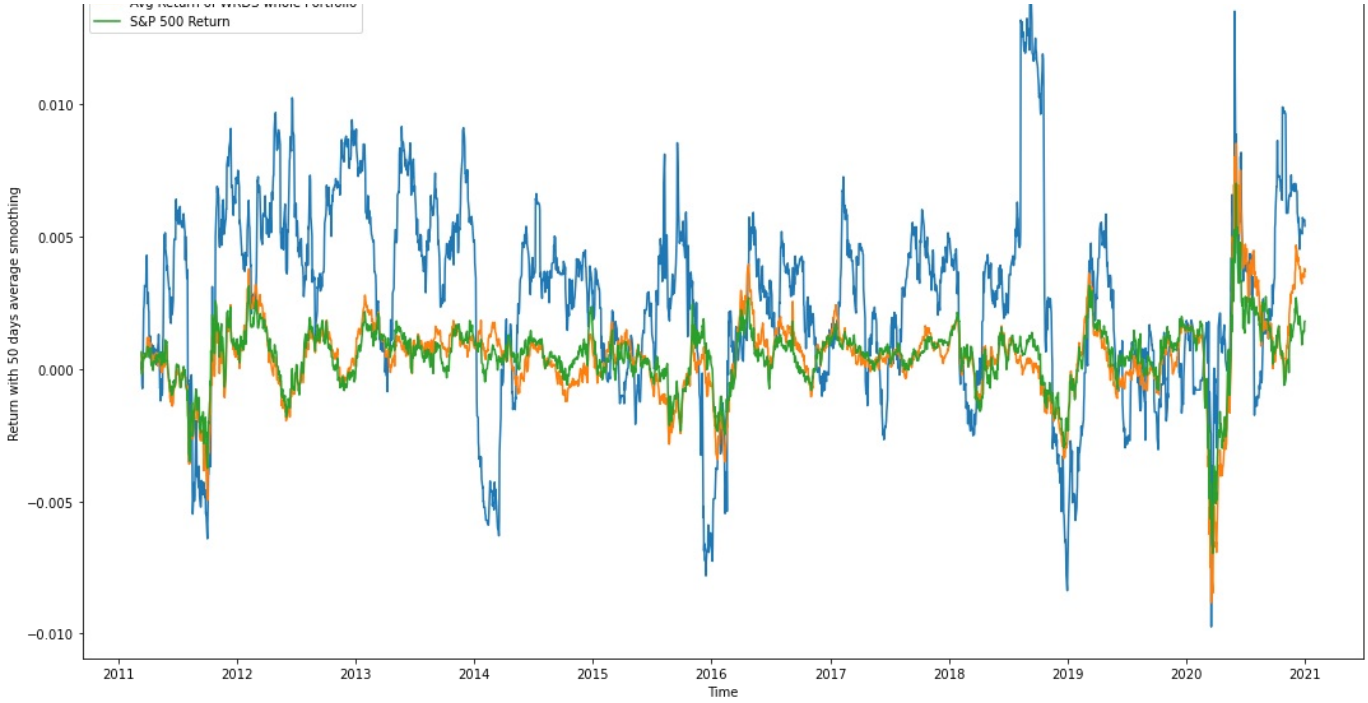
In [18]:
```
(df_result['OUR_RET'].mean() / df_result['OUR_RET'].std()) * np.sqrt(250)
```

Out[18]:
```
1.5388420045014588
```

Visualization:

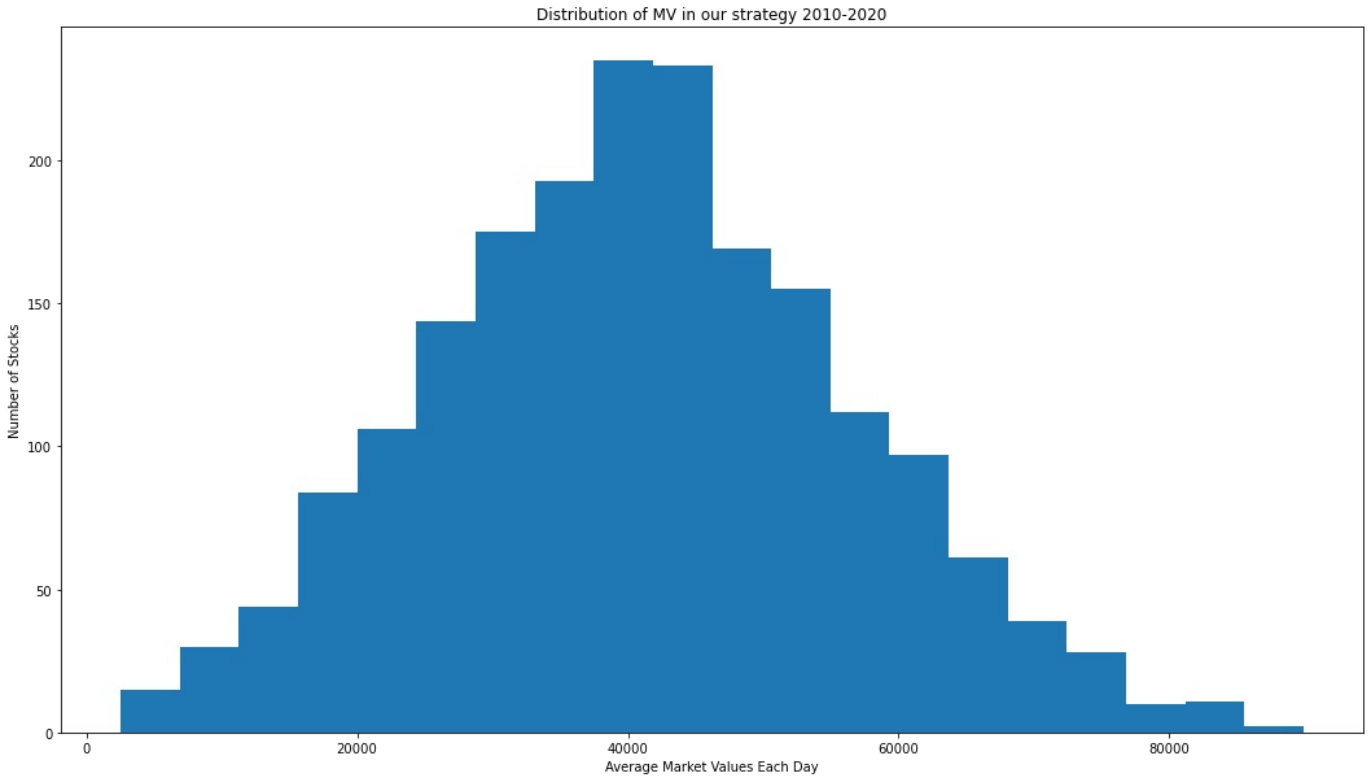
In [19]:
```
plt.figure(figsize=(18,10))
plt.title("Return Comparison")
plt.xlabel('Time')
plt.ylabel('Return with 50 days average smoothing')
plt.plot(df_result['OUR_RET'].rolling(50).mean(), label = "Our Strategy Return")
plt.plot(df_result['XRET'].rolling(50).mean(), label = "Avg Return of WRDS whole Portfolio")
plt.plot(df_result['S&P Ret'].rolling(50).mean(), label = "S&P 500 Return")
plt.legend()
plt.show()
```





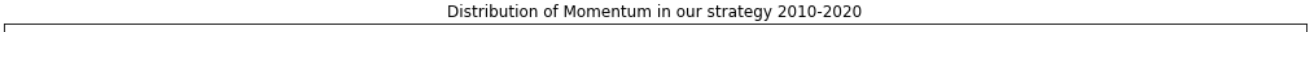
In [20]:

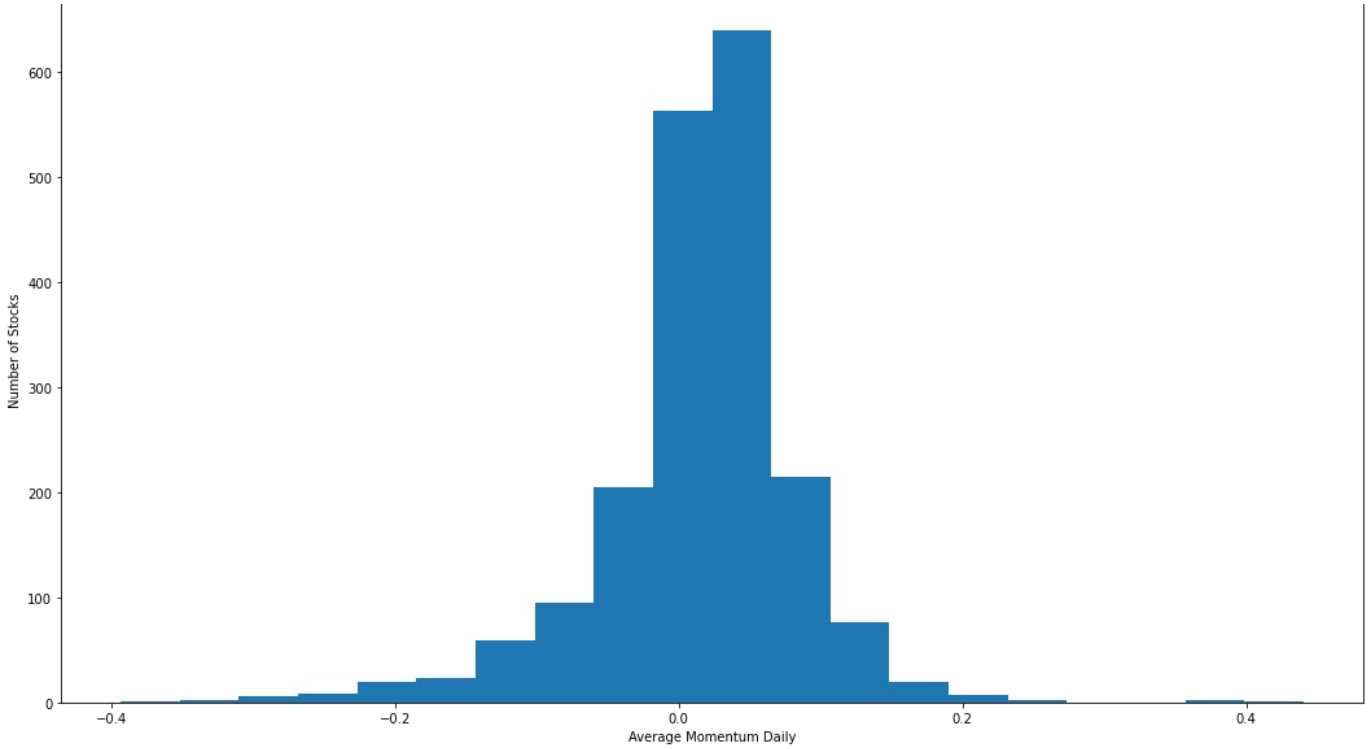
```
df_for_plot = data_2.loc[ (data_2['QUINTILE_ma'] == 1) &
                 (data_2['QUINTILE_mom'] == 3) &
                 (data_2['QUINTILE_mv'] == 1) &
                 (data_2['QUINTILE_id'] == 1) &
                 (data_2['LAG_VOL'] >= 5000), ].groupby('DATE').mean()

plt.figure(figsize=(18,10))
plt.hist(df_for_plot['MV'],bins=20)
plt.title("Distribution of MV in our strategy 2010-2020")
plt.xlabel('Average Market Values Each Day')
plt.ylabel('Number of Stocks')
plt.show()
```



In [21]:

```
plt.figure(figsize=(18,10))
plt.hist(df_for_plot['MOMENTUM'],bins=20)
plt.title("Distribution of Momentum in our strategy 2010-2020")
plt.xlabel('Average Momentum Daily')
plt.ylabel('Number of Stocks')
plt.show()
```





- Our strategy yield extremely high return with higher variations.