momentum

December 24, 2020

[1]:
```
import numpy as np
import pandas as pd
from pandas.tseries.offsets import MonthEnd, YearEnd
import datetime as dt
import matplotlib.pyplot as plt
import os
os.chdir("/Users/charlesrambo/Desktop/QIII/Quantitative Asset Management")
```

[2]:
```
# Load stock information
stocks = pd.read_csv("stocks.csv")
```

[3]:
```
# Record CRSP unkowns
unknowns = ["-66.0", "-77.0", "-88.0", "-99.0", "-99.99", "-999", "A", "B",␣
↪"C", "D", "E", "S", "T", "P"]

# Create function to convert CRISP unkowns to np.nan
convert_unknows = lambda x: np.nan if x in unknowns else x
```

[4]:
```
# Convert date column to date-time object
stocks['date'] = pd.to_datetime(stocks['date'], format = '%Y%m%d')

# Record observations where both returns and delisting returns are missing
stocks['flag'] = stocks['RET'].isna() & stocks['DLRET'].isna()

# Fill missing returns with 0
stocks['RET'] = stocks['RET'].apply(convert_unknows).astype(float).fillna(0)

# Fill missing delisting returns with 0
stocks['DLRET'] = stocks['DLRET'].apply(convert_unknows).astype(float).fillna(0)

# Compute log returns of the product
stocks['RET'] = np.log((1 + stocks['RET']) * (1 + stocks['DLRET']))

#Make stale prices positive
stocks['PRC'] = stocks['PRC'].abs()

# Remove 0 priced observations
```

```
stocks = stocks.loc[stocks['PRC'] > 0]

# Remove non-psitive shares outstanding
stocks = stocks.loc[stocks['SHROUT'] > 0]

# Only consider stocks listed on the big exchanges
stocks = stocks.loc[stocks['SHRCD'].isin([10, 11]) & stocks['EXCHCD'].isin([1,␣
↪2, 3])]

# Drop unneeded columns
stocks.drop(['DLRET', 'SHRCD', 'EXCHCD', 'PERMCO'], axis = 1, inplace = True)
```

```
/Users/charlesrambo/opt/anaconda3/lib/python3.7/site-
packages/pandas/core/series.py:679: RuntimeWarning: divide by zero encountered
in log
  result = getattr(ufunc, method)(*inputs, **kwargs)
```

[5]:

```
# Calculate market equity
stocks['ME'] = stocks['PRC'] * stocks['SHROUT']

# Short values for shift
stocks.sort_values(by = ['PERMNO', 'date'], inplace = True)

# Record the shifts which are valid
stocks['Isvalid'] = stocks['date'] + MonthEnd(0) == stocks['date'].shift(1) +␣
↪dt.timedelta(days = 7) + MonthEnd(0)
stocks.loc[stocks['Isvalid'] == True, 'Isvalid'] = stocks.loc[stocks['Isvalid']␣
↪== True, 'PERMNO'] == stocks.loc[stocks['Isvalid'] == True, 'PERMNO'].
↪shift(1)

# Shift market equity
stocks['ME_lag'] = stocks[['PERMNO', 'ME']].groupby('PERMNO')['ME'].shift(1)

# Replace the invalids with nan
stocks.loc[stocks['Isvalid'] == False, 'ME_lag'] = np.nan

# Drop unneeded columns
stocks.drop(['ME', 'Isvalid'], axis = 1, inplace = True)
```

[6]:

```
# Sort values again for another shift
stocks.sort_values(by = ['PERMNO', 'date'], inplace = True)

# Check to see if valid
stocks['Isvalid'] = stocks['date'] + MonthEnd(0) == stocks['date'].shift(12) +␣
↪dt.timedelta(days = 7) + MonthEnd(12)
```

```python
stocks.loc[stocks['Isvalid'] == True, 'Isvalid'] = stocks.loc[stocks['Isvalid']␣
↪== True, 'PERMNO'] == stocks.loc[stocks['Isvalid'] == True, 'PERMNO'].
↪shift(12)

# Calculate momentum signal
stocks['MOM'] = stocks['RET'].shift(2).rolling(11).sum()

# Remove invalid observations
stocks.loc[stocks['Isvalid'] == False, 'MOM'] = np.nan

# Convert infinite returns to na
stocks['RET'] = stocks['RET'].replace([np.inf, -np.inf], np.nan)

# Remove observations with missing momentum signal
stocks = stocks.loc[stocks['MOM'].notna() & ~stocks['flag'], :]

# Place firms into deciles based on momentum signal
stocks['decile'] = stocks[['date', 'MOM']].groupby('date').transform(lambda x:␣
↪pd.qcut(x, 10, labels = False))

# Drop uneeded columns
stocks.drop(['Isvalid', 'PRC', 'SHROUT', 'PERMNO', 'MOM', 'flag'], axis = 1,␣
↪inplace = True)
```

[7]:
```python
# Compute weights for returns; value weighted
stocks['wt'] = stocks.groupby(['date', 'decile'])['ME_lag'].transform('sum')
stocks['wt'] = stocks['ME_lag']/stocks['wt']

# Weight returns
stocks['RET'] = stocks['RET'] * stocks['wt']

# Compute sume
W = stocks[['date', 'decile', 'RET']].groupby(['date', 'decile'])['RET'].sum().
↪reset_index()

# Add 1 to deciles to avoid confusion
W['decile'] = 1 + W['decile']

# Undo log return calculate
W['RET'] = W['RET'].apply(np.exp) - 1

W.head()
```

[7]:

	date	decile	RET
0	1974-12-31	1	-0.057489
1	1974-12-31	2	-0.047717
2	1974-12-31	3	-0.071430

```
3 1974-12-31       4 -0.037651
4 1974-12-31       5 -0.040343
```

[8]:
```python
# Make each decile its own column
deciles = W.pivot(index = 'date', columns = 'decile', values = 'RET').
↪reset_index()

# Calculate winners minus losers
deciles['wml'] = deciles[10] - deciles[1]

deciles.head()
```

[8]:
```
decile        date         1         2         3         4         5         6  \
0       1974-12-31 -0.057489 -0.047717 -0.071430 -0.037651 -0.040343 -0.022080
1       1975-01-31  0.298759  0.280975  0.185028  0.112457  0.147705  0.104635
2       1975-02-28  0.052432  0.066288  0.063239  0.030882  0.097922  0.034669
3       1975-03-31  0.082226  0.056961  0.023014  0.047053  0.029042  0.013761
4       1975-04-30  0.025278  0.047257  0.067493  0.033242  0.060814  0.052070

decile         7         8         9        10       wml
0       -0.021311 -0.018940  0.004415 -0.036807  0.020683
1        0.071509  0.092411  0.124303  0.112269 -0.186490
2        0.066664  0.058126  0.050050  0.035779 -0.016653
3        0.021114 -0.001186  0.040525  0.070834 -0.011392
4        0.026981  0.039376  0.025009  0.072989  0.047711
```

[9]:
```python
stats = pd.DataFrame(index = deciles.columns[1:])

# Take a look at the mean
stats['mean'] = deciles.mean()

# Take a look at the sd
stats['sd'] = deciles.std()

# Take a look at the skew
stats['skew'] = deciles.skew()

stats
```

[9]:
```
            mean        sd      skew
decile
1      -0.010669  0.094376  0.364164
2      -0.001330  0.071832 -0.255874
3       0.004277  0.061145 -0.149047
4       0.006855  0.050992 -0.336989
5       0.008173  0.047060 -0.411477
6       0.007505  0.043465 -0.506360
```

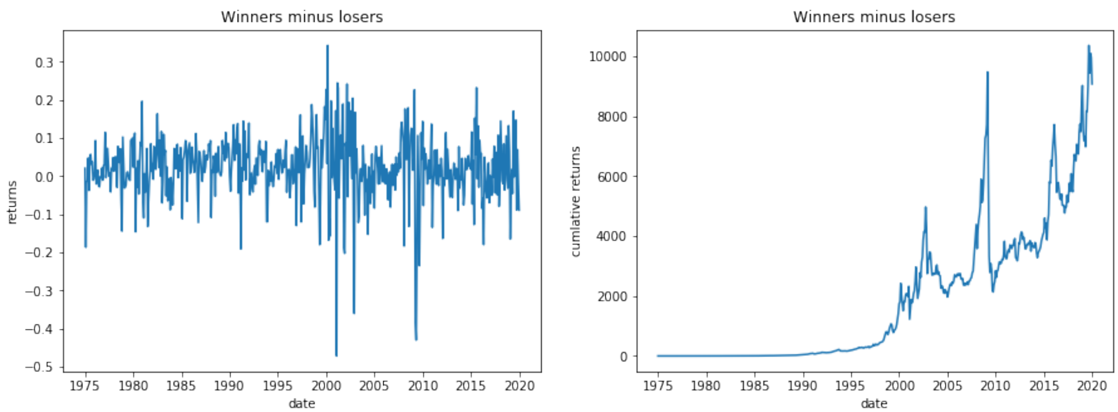
```
7        0.009008  0.043080 -0.613381
8        0.009998  0.045753 -0.585472
9        0.009703  0.050553 -0.740854
10       0.010088  0.066374 -0.432244
wml      0.020757  0.084046 -0.998041
```

[10]:

```
# Plot returns
fig, (ax1, ax2) = plt.subplots(1, 2, figsize = (15,5))
ax1.plot(deciles['date'], deciles["wml"])
ax1.set_xlabel('date')
ax1.set_ylabel('returns')
ax1.set_title('Winners minus losers')

ax2.plot(deciles['date'], (1 + deciles["wml"]).cumprod() - 1)
ax2.set_xlabel('date')
ax2.set_ylabel('cumlative returns')
ax2.set_title('Winners minus losers')

plt.show()
```



[11]:

```
# Load Daniel's momentum
daniel = pd.read_csv("m_m_pt_tot.csv", header = None)
daniel.rename(columns = {0:"date", 1:"decile", 2:"ret", 3:"avg_me", 4:"firms"},␣
 ↪inplace = True)
daniel['date'] = pd.to_datetime(daniel['date'], format = '%Y%m%d')
daniel.drop(['avg_me', 'firms'], axis = 1, inplace = True)

daniel = daniel.pivot(index = 'date', columns = 'decile', values = 'ret').
 ↪reset_index()
daniel['wml'] = daniel[10] - daniel[1]

daniel.head()
```

[11]:
```
decile        date        1        2        3        4        5        6  \
0       1927-01-31 -0.03362 -0.04584  0.02755 -0.00319 -0.00294  0.00893
1       1927-02-28  0.07627  0.05984  0.08206  0.07271  0.03510  0.03040
2       1927-03-31 -0.03003 -0.03055 -0.03914 -0.04880 -0.00540 -0.02391
3       1927-04-30  0.02042 -0.03130 -0.02379 -0.01262  0.01977 -0.00058
4       1927-05-31  0.03949  0.04313  0.06097  0.03178  0.06337  0.05800

decile        7        8        9       10      wml
0       0.00781  0.00359 -0.00375 -0.00225  0.03137
1       0.04012  0.03257  0.04169  0.07007 -0.00620
2       0.02067  0.00850 -0.00034  0.06091  0.09094
3       0.02094 -0.00930  0.01809  0.05489  0.03447
4       0.05219  0.06671  0.08051  0.06231  0.02282
```

[12]:
```python
# See correlation; not perfect because momentum construction (intentionally)␣
 ↪not exactly same
results = deciles.merge(daniel, on = 'date')

round(results.corr().iloc[0:11 , 11:], 3)
```

[12]:
```
decile    1_y    2_y    3_y    4_y    5_y    6_y    7_y    8_y    9_y   10_y  \
decile
1_x     0.986  0.912  0.863  0.804  0.761  0.714  0.621  0.577  0.522  0.495
2_x     0.875  0.979  0.921  0.871  0.831  0.793  0.687  0.636  0.569  0.497
3_x     0.841  0.921  0.989  0.922  0.884  0.840  0.729  0.672  0.583  0.491
4_x     0.783  0.865  0.908  0.989  0.919  0.886  0.805  0.748  0.629  0.521
5_x     0.736  0.819  0.869  0.906  0.992  0.918  0.862  0.819  0.727  0.604
6_x     0.680  0.768  0.827  0.880  0.907  0.994  0.920  0.895  0.796  0.669
7_x     0.606  0.667  0.728  0.800  0.857  0.915  0.997  0.935  0.865  0.732
8_x     0.552  0.614  0.669  0.737  0.814  0.893  0.934  0.997  0.904  0.783
9_x     0.516  0.550  0.586  0.633  0.723  0.793  0.864  0.907  0.997  0.883
10_x    0.496  0.487  0.503  0.531  0.609  0.681  0.746  0.799  0.897  0.996
wml_x  -0.710 -0.634 -0.566 -0.478 -0.368 -0.259 -0.102 -0.011  0.130  0.238

decile  wml_y
decile
1_x    -0.729
2_x    -0.603
3_x    -0.570
4_x    -0.482
5_x    -0.366
6_x    -0.253
7_x    -0.121
8_x    -0.022
9_x     0.094
10_x    0.204
wml_x   0.980
```