# momentum

December 25, 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)
```

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

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

# 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']

W.head()
```

[7]:

| | date | decile | RET |
|---|---|---|---|
| 0 | 1974-12-31 | 1 | -0.048996 |
| 1 | 1974-12-31 | 2 | -0.042374 |
| 2 | 1974-12-31 | 3 | -0.067604 |

```
3 1974-12-31       4 -0.034328
4 1974-12-31       5 -0.038449
```

[8]:
```
# 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 -0.048996 -0.042374 -0.067604 -0.034328 -0.038449 -0.019007
1      1975-01-31  0.312802  0.292749  0.191119  0.127405  0.153141  0.116497
2      1975-02-28  0.064369  0.078503  0.068191  0.035711  0.102296  0.037761
3      1975-03-31  0.093321  0.067232  0.027116  0.050056  0.032083  0.015749
4      1975-04-30  0.035966  0.054807  0.074085  0.039255  0.067083  0.055308

decile         7         8         9        10       wml
0      -0.017899 -0.017098  0.007226 -0.033485  0.015511
1       0.081780  0.096964  0.129181  0.119560 -0.193242
2       0.070395  0.061465  0.052745  0.038628 -0.025742
3       0.024145  0.001187  0.043431  0.075229 -0.018091
4       0.028890  0.042888  0.028106  0.077720  0.041754
```

[9]:
```
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
```

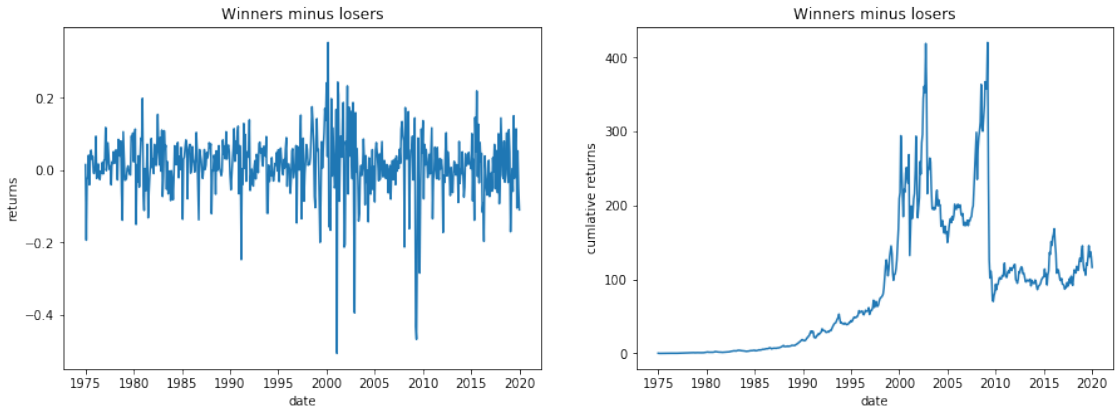
[9]:
```
            mean        sd      skew
decile
1       0.002733  0.095029  0.697348
2       0.005453  0.071070  0.087736
3       0.008361  0.060592  0.086449
4       0.009974  0.050797 -0.145486
5       0.010755  0.046773 -0.265526
6       0.009798  0.043178 -0.409866
```

```
7       0.011254  0.042968 -0.555850
8       0.012453  0.045544 -0.519261
9       0.012826  0.050282 -0.650857
10      0.015607  0.066559 -0.276098
wml     0.012874  0.085530 -1.251917
```

[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]:
```
# 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     0.989  0.909  0.858  0.802  0.756  0.706  0.612  0.565  0.508  0.486
2_x     0.886  0.987  0.930  0.881  0.836  0.796  0.691  0.635  0.565  0.494
3_x     0.842  0.922  0.990  0.923  0.885  0.840  0.728  0.669  0.578  0.488
4_x     0.783  0.866  0.909  0.991  0.921  0.885  0.803  0.743  0.624  0.516
5_x     0.739  0.822  0.871  0.907  0.992  0.919  0.862  0.817  0.723  0.602
6_x     0.679  0.769  0.826  0.879  0.908  0.995  0.922  0.895  0.798  0.671
7_x     0.605  0.668  0.728  0.799  0.857  0.915  0.998  0.935  0.864  0.732
8_x     0.549  0.614  0.667  0.735  0.812  0.893  0.935  0.998  0.905  0.784
9_x     0.515  0.550  0.585  0.631  0.722  0.793  0.865  0.908  0.998  0.886
10_x    0.491  0.483  0.498  0.524  0.603  0.675  0.741  0.795  0.895  0.998
wml_x  -0.712 -0.629 -0.560 -0.479 -0.365 -0.254 -0.097 -0.004  0.138  0.242

decile  wml_y
decile
1_x    -0.740
2_x    -0.618
3_x    -0.573
4_x    -0.485
5_x    -0.370
6_x    -0.251
7_x    -0.121
8_x    -0.018
9_x     0.099
10_x    0.211
wml_x   0.985
```