Analysis of Fixed Income Securities

In [2]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
```

```
D:\Python\bondProjectLocal\lib\site-packages\numpy\_distributor_init.py:30: UserWarning:
loaded more than 1 DLL from .libs:
D:\Python\bondProjectLocal\lib\site-packages\numpy\.libs\libopenblas.WCDJNK7YVMPZQ2ME2ZZ
HJJRJ3JIKNDB7.gfortran-win_amd64.dll
D:\Python\bondProjectLocal\lib\site-packages\numpy\.libs\libopenblas.QVLO2T66WEPI7JZ63PS
3HMOHFEY472BC.gfortran-win_amd64.dll
  warnings.warn("loaded more than 1 DLL from .libs:"
```

In [3]:
```
df = pd.read_csv('ctap_analytics_pnl_decomp_sample_day.csv')
df['timestamp'] = pd.to_datetime(df['timestamp'])
```

Data exploration

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

Out[4]:

	timestamp	type	cusip	spread_pnl	benchmark_cusip	new_position	ticker	securitydes	indus
0	2021-07-28 06:00:00	MARK	718172CQ0	-0.618819	91282CCK5	-39	PM	PM 1 1/8 05/01/23	N
1	2021-07-28 06:00:00	MARK	718172CQ0	-0.618819	91282CCK5	-39	PM	PM 1 1/8 05/01/23	N
2	2021-07-28 06:00:00	MARK	03073EAS4	0.060743	91282CCK5	5	ABC	ABC 0.737 03/15/23	N
3	2021-07-28 06:00:00	MARK	723484AH4	0.291196	91282CCJ8	-13	PNW	PNW 1.3 06/15/25	
4	2021-07-28 06:00:00	MARK	742718ER6	-0.212672	91282CCJ8	2	PG	PG 2.45 11/03/26	N

Duplicate data

I have found that there is one observation that is a duplicate

In [5]:
```
beginning_len = len(df)
dropped_len = len(df.drop_duplicates())
print(f'The dataframe began with {beginning_len} observations and then, after dropping
```

```
The dataframe began with 55718 observations and then, after dropping duplicates, we were
left with 55717 observations.
```

Data modification

I have decided to slightly modify the dataset to address my findings in the data exploration section. Namely, I have done the following:

- Drop the duplicated observation

Drop duplicates

I am dropping the duplicate values, as we only need one observation for a given timestamp/CUSIP combination

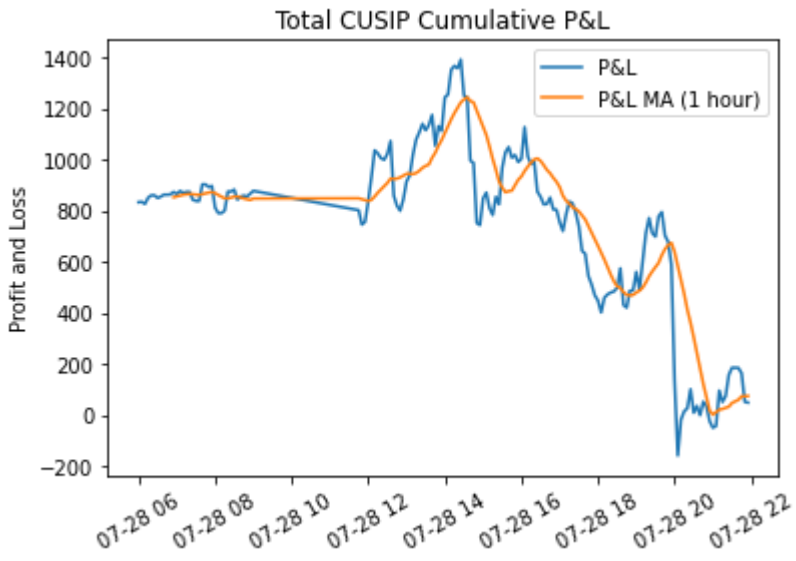
In [6]:
```
df = df.drop_duplicates()
```

Analysis

Overall profit and loss across all CUSIPs throughout time

In [7]:
```
cumulative_spread_pnl = np.cumsum(df.groupby('timestamp')['spread_pnl'].sum())
cumulative_spread_pnl_MA = cumulative_spread_pnl.rolling(12).mean()
plt.plot(cumulative_spread_pnl, label='P&L')
plt.plot(cumulative_spread_pnl_MA, label='P&L MA (1 hour)')
plt.xticks(rotation=30)
plt.ylabel('Profit and Loss')

plt.legend()
plt.title('Total CUSIP Cumulative P&L')
plt.show()
```



CUSIPs with large losses and gains over entire range

In [8]:
```
n_cusips = 30

cumulative = df.groupby(['cusip', 'timestamp'])['spread_pnl'].sum().groupby(level=0).cu
```

```
cumulative.columns = ['cusip', 'timestamp', 'cumulative_pnl']

df = pd.merge(df, cumulative, on=['timestamp', 'cusip'])
```

In [9]:
```
difference_cumulative = (df.groupby('cusip')['cumulative_pnl'].last() - df.groupby('cus
difference_cumulative = difference_cumulative.sort_values()
winners = difference_cumulative[-n_cusips:].iloc[::-1]
losers = difference_cumulative[:n_cusips]
```

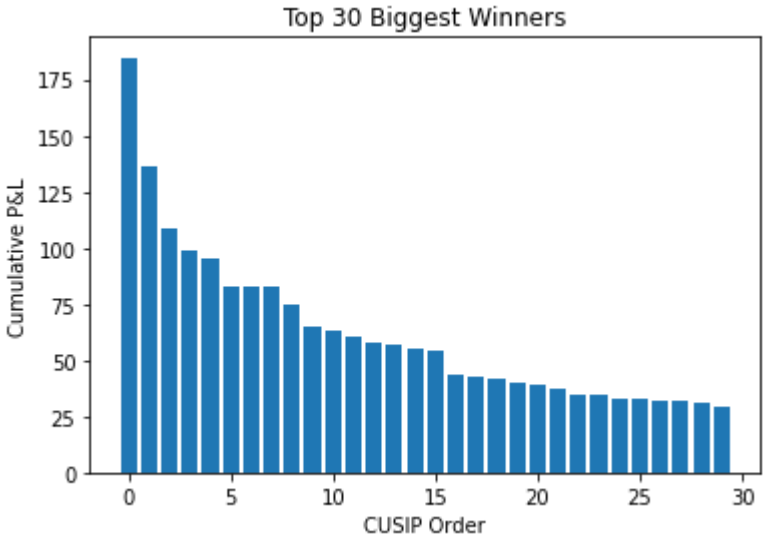
In [10]:
```
winners.reset_index()
```

Out[10]:

	cusip	cumulative_pnl
0	742718FG9	184.745510
1	68389XBL8	135.933830
2	89236THG3	108.464667
3	00914AAH5	98.849109
4	302635AG2	94.946352
5	46124HAA4	83.226557
6	928668BL5	83.204654
7	46625HRV4	83.063795
8	281020AN7	75.086144
9	6174467X1	64.889666
10	023135AZ9	63.470965
11	517834AE7	60.884837
12	00206RDQ2	58.022936
13	833794AA8	56.836172
14	29278NAM5	55.531123
15	778296AF0	54.239155
16	037833DX5	43.377159
17	40434LAB1	42.325347
18	760759AU4	41.875580
19	06367WB85	40.202744
20	037833CG3	38.640763
21	03027XAK6	36.996955
22	097023CT0	34.331433
23	337738AS7	34.302991
24	92343EAH5	33.176490
25	928563AC9	32.640242

	cusip	cumulative_pnl
26	20030NBS9	31.672196
27	60871RAG5	31.644484
28	594918BX1	30.972719
29	037833AS9	29.034911

In [11]:
```
plt.bar(list(range(n_cusips)), winners.reset_index()['cumulative_pnl'])
plt.xlabel('CUSIP Order')
plt.ylabel('Cumulative P&L')
plt.title(f'Top {n_cusips} Biggest Winners')
plt.show()
```



In [12]:
```
losers.reset_index()
```

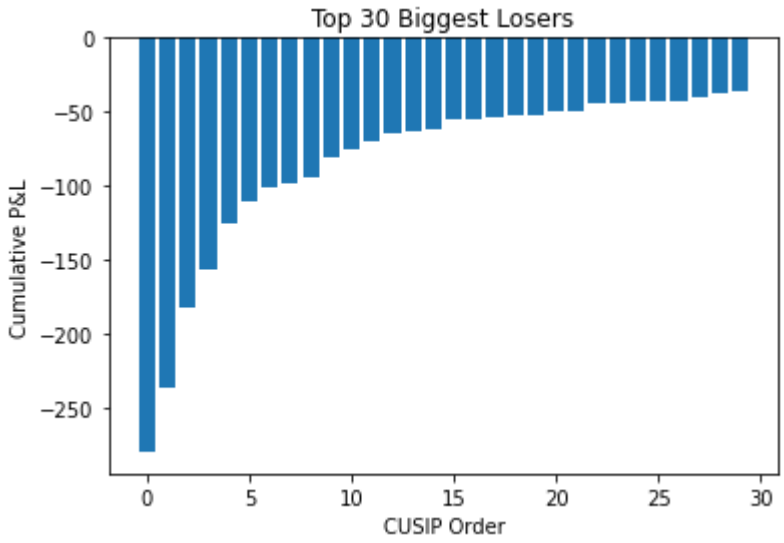
Out[12]:

	cusip	cumulative_pnl
0	254709AM0	-279.984222
1	92826CAP7	-236.284840
2	745867AX9	-182.323575
3	785592AS5	-156.907800
4	78013XW20	-125.216640
5	172967KA8	-110.204121
6	291011BP8	-101.288510
7	87612EBD7	-98.693604
8	437076BC5	-93.768223
9	89788MAC6	-80.512902
10	166764BT6	-75.046221

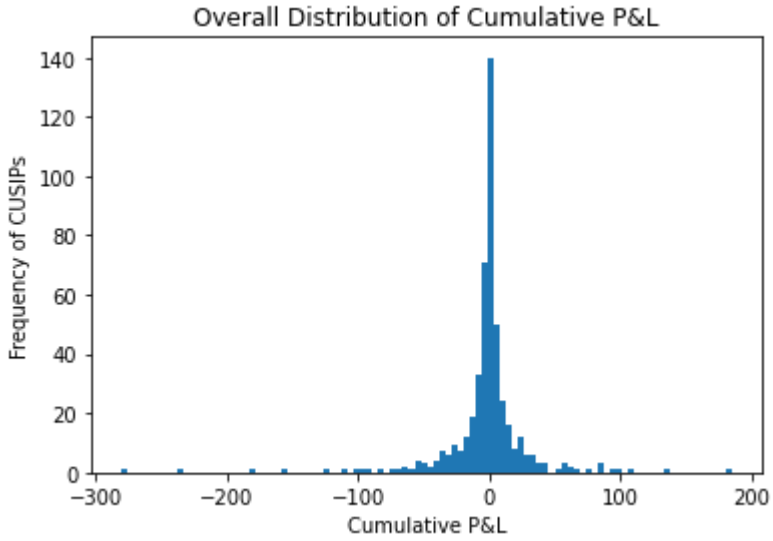
	cusip	cumulative_pnl
11	56585ABG6	-69.324519
12	35137LAG0	-64.773134
13	126650CU2	-63.300262
14	911312BX3	-61.515108
15	94974BGL8	-55.514089
16	22822VAV3	-55.502122
17	92343VDD3	-53.028700
18	59156RBH0	-52.296703
19	25389JAR7	-52.100353
20	101137AV9	-49.999962
21	418056AY3	-49.849194
22	637639AA3	-44.034765
23	91324PDE9	-43.578632
24	871829BP1	-42.961674
25	37045XDK9	-42.603880
26	902494BJ1	-42.587259
27	06051GFU8	-39.497122
28	717081DM2	-37.217739
29	478160CN2	-36.647996

In [58]:

```
plt.bar(list(range(n_cusips)), losers.reset_index()['cumulative_pnl'])
plt.xlabel('CUSIP Order')
plt.ylabel('Cumulative P&L')
plt.title(f'Top {n_cusips} Biggest Losers')
plt.show()
```



In [64]:
```
plt.hist(difference_cumulative, bins=100)
plt.title('Overall Distribution of Cumulative P&L')
plt.ylabel('Frequency of CUSIPs')
plt.xlabel('Cumulative P&L')
plt.show()
```

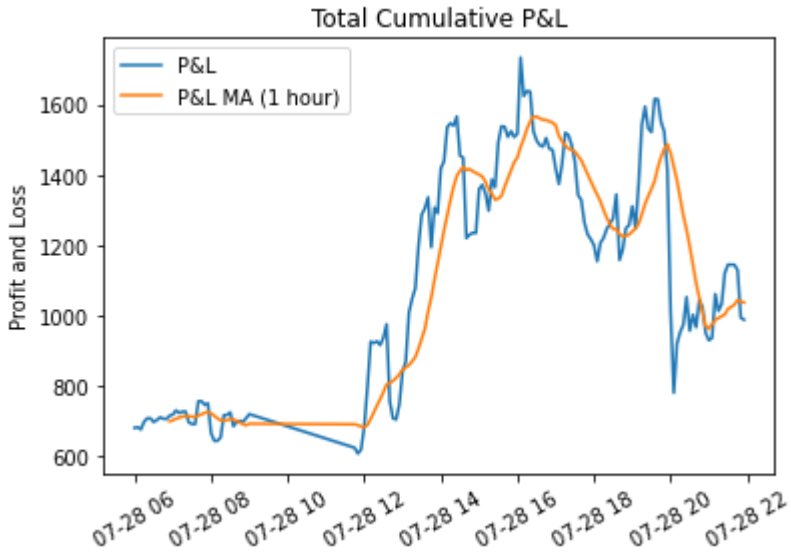


P&L Total Excluding Top 6 Losers

In [26]:
```
excluded_cusips = ['254709AM0', '92826CAP7', '745867AX9', '785592AS5', '78013XW20', '17
excluded = df[~df['cusip'].isin(excluded_cusips)]

cumulative_spread_pnl = np.cumsum(excluded.groupby('timestamp')['spread_pnl'].sum())
cumulative_spread_pnl_MA = cumulative_spread_pnl.rolling(12).mean()
plt.plot(cumulative_spread_pnl, label='P&L')
plt.plot(cumulative_spread_pnl_MA, label='P&L MA (1 hour)')
plt.xticks(rotation=30)
plt.ylabel('Profit and Loss')

plt.legend()
plt.title('Total Cumulative P&L')
plt.show()
```



What is the commonality between these losing securities?

Seems like this might have been a bad day for financials. Two to six-years to maturity is also a common characteristic.

In [27]:
```
df[df['cusip'].isin(excluded_cusips)][['type', 'cusip', 'benchmark_cusip', 'new_positio
```

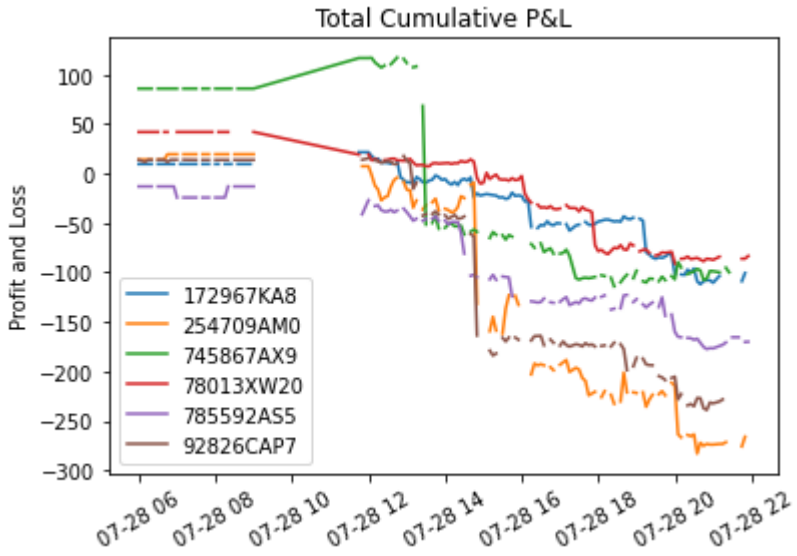
Out[27]:

	type	cusip	benchmark_cusip	new_position	ticker	securitydes	industrySector	mat_bu
4	MARK	745867AX9	91282CCJ8	-100	PHM	PHM 5 01/15/27	Consumer, Cyclical	
30	MARK	785592AS5	91282CCJ8	-90	SPLLLC	SPLLLC 5 03/15/27	Energy	
43	MARK	78013XW20	91282CCK5	85	RY	RY 3.7 10/05/23	Financial	
132	MARK	92826CAP7	91282CCJ8	-60	V	V 0 3/4 08/15/27	Financial	
234	MARK	254709AM0	91282CCJ8	-224	DFS	DFS 4.1 02/09/27	Financial	
276	MARK	172967KA8	91282CCJ8	-72	C	C 4.45 09/29/27	Financial	
24899	MARK	78013XW20	91282CCK5	150	RY	RY 3.7 10/05/23	Financial	
32781	MARK	78013XW20	91282CCK5	163	RY	RY 3.7 10/05/23	Financial	
38752	MARK	78013XW20	91282CCK5	176	RY	RY 3.7 10/05/23	Financial	

In [30]:
```
ex = df[df['cusip'].isin(excluded_cusips)]
ex = ex.groupby(['cusip', 'timestamp'])['cumulative_pnl'].sum().unstack().T
```

```
plt.plot(ex)
plt.xticks(rotation=30)
plt.ylabel('Profit and Loss')

plt.legend(ex.columns)
plt.title('Total Cumulative P&L')
plt.show()
```



What happend to Royal Bank of Canada (RY)?

On July 28th, Royal Bank of Canada issued 650 million new senior floating notes due in 2024 and 850 million senior fixed notes at 0.650%. This could have devalued these existing bonds because issuing over a billion in new debt could indicate rising credit risk. Yields for this bank could have increased, causing P&L for the CUSIPs in the portfolio to decrease.

Market driven or company driven?

- DFS is a lower medium grade bond
- RBC is upper medium grade bond
- C is a lower medium grade bond
- V is a high grade bond

Market yields for this time period went down. Perhaps these securities were not as in demand due to their credit ratings. The continuation of this downward trend could be due to a market desire to be in less risky securities at this time.