This notebook goes through building out a data set that is useful for future ML projects around Post Earnings short term trading from 2010 to 2024 by making SQL queries to wrds data base to grab:

-Analyst estimates and actuals, along with number of estimates (IBES) -Company Industries (really sector but IBES calls sectors industries) -Analyst buy hold sell percent recommendations along with number of analysts (IBES)

- Open and close data and shares outstanding (CRSP)
- SP500 constituents over time (CRSP)

At the bottom I perform a ***Gradient Boosting Classification*** model on stock returns from t = 0 close to t = 1 close, where t = 0 represents the day the markets reacted to the earnings. Subjects will be grouped into long, shorts, and flats then the model and their returns will be analyzed. This data will also be used for future projects, which is why there are some unused features such as different return horizons.

Below is just pulling in data using SQL queries.

IMPORTANT NOTE

Feel free to ***skip down to the cell that says END DATA PULLING***. You can just do ctrl f and paste this in: END OF DATA PULLING

Connecting to the SQL database

In [1]:
```
import wrds

db = wrds.Connection()
```

```
Loading library list...
Done
```

Grabbing tickers in SP500 from 2010 to 2024 from CRSP

In [2]:
```
import pandas as pd
beg_datestr = '01-01-2010'
end_datestr = '01-15-2025'
begdate = pd.to_datetime(beg_datestr)
```

```
enddate = pd.to_datetime(end_datestr)



sp500 = db.raw_sql(f"""
                        select a.*
                        from crsp.msp500list as a;
                        """, date_cols=['start', 'ending'])
sp500 = sp500[sp500['ending']>=begdate]
sp500.reset_index(drop=True, inplace = True)
sp500
```

Out[2]:

	permno	start	ending
0	10078	1992-08-20	2010-01-28
1	10104	1989-08-03	2024-12-31
2	10107	1994-06-07	2024-12-31
3	10137	2000-12-11	2011-02-25
4	10138	1999-10-13	2024-12-31
...	...	...	...
823	93159	2012-07-31	2016-03-29
824	93246	2021-03-22	2024-12-31
825	93422	2010-07-01	2015-06-30
826	93429	2017-03-01	2024-12-31
827	93436	2020-12-21	2024-12-31

828 rows × 3 columns

permno is a unique identifier that every stock ever has been assigned by CRSP. To get the Earnings estimates and actuals data we need to pull from the IBES database which has thier own unique identifier called a ticker. WRDS provides a program that outputs a csv that maps these two identifiers and scores the confidence of the mapping.

In [3]:

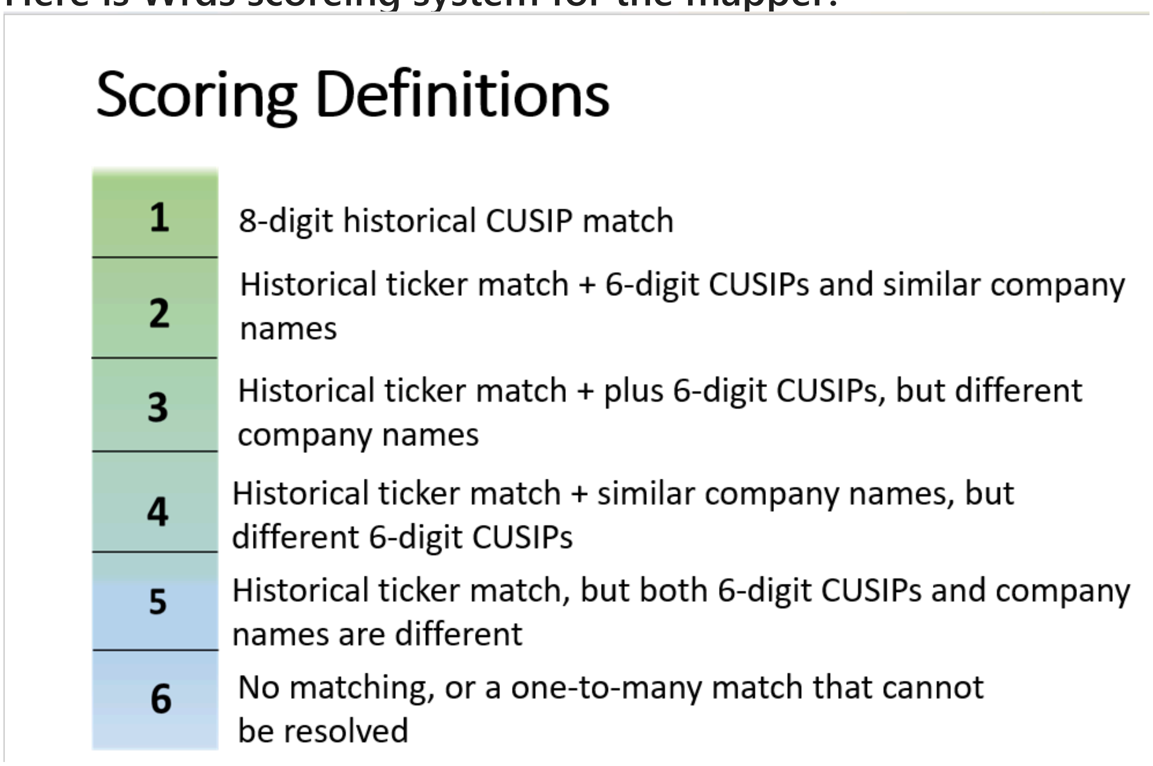
```
mapper = pd.read_csv('iclink.csv')
mapper.set_index('permno', inplace = True, drop = True)
mapper = mapper[mapper.index.isin(set(sp500['permno'].to_list()))]
mapper
```

Out[3]:

permno	ticker	cname	comnam	name_ratio	score
14579	003H	PAYCOM SOFTWARE	PAYCOM SOFTWARE INC	100.0	0
14714	004W	ARISTA NETWORKS	ARISTA NETWORKS INC	100.0	0
14939	00C6	KEYSIGHT TECH	KEYSIGHT TECHNOLOGIES INC	76.0	0
15850	00WY	MATCH GRP	MATCH GROUP INC NEW	71.0	0
16342	01AB	ADIENT	ADIENT PLC	100.0	0
...	...	...	...	...	...
89070	ZMH	ZIMMER BIOMET	ZIMMER BIOMET HOLDINGS INC	100.0	0
13788	ZOTS	ZOETIS	ZOETIS INC	100.0	0
40539	ZY	TJX	T J X COMPANIES INC NEW	15.0	1
70519	CICA	CITI CAP	CITIGROUP INC	NaN	6
49015	LINA	LINCOLN NAT CAP	LINCOLN NATIONAL CORP	NaN	5

831 rows × 5 columns

Here is Wrds scoreing system for the mapper:



. Meaning we are only concerned with 3, 4, 5, or 6 scored matches, so we will take a look at those below

In [4]:

```
low_confidence_maps = mapper[mapper['score'] >2]
```

```
low_confidence_maps
```

Out[4]:

	ticker	cname	comnam	name_ratio	score
permno					
70519	CICA	CITI CAP	CITIGROUP INC	NaN	6
49015	LINA	LINCOLN NAT CAP	LINCOLN NATIONAL CORP	NaN	5

In looking at the names it seems fair to leave them in the dataset and assume they are correct.

Creating a Map from permno to ticker and adding ticker to the sp500 dataset

In [5]:

```
ticker_mapper = mapper['ticker'].to_dict()
name_mapper = mapper['cname'].to_dict()
sp500['ticker'] = sp500['permno'].map(ticker_mapper)
sp500['cname'] = sp500['permno'].map(name_mapper)
sp500
```

Out[5]:

	permno	start	ending	ticker	cname
0	10078	1992-08-20	2010-01-28	SUNW	SUN MICROSYSTEMS
1	10104	1989-08-03	2024-12-31	ORCL	ORACLE
2	10107	1994-06-07	2024-12-31	MSFT	MICROSOFT
3	10137	2000-12-11	2011-02-25	AYP	ALLEGHENY ENERGY
4	10138	1999-10-13	2024-12-31	PTRW	T ROWE PRICE GRP
...	...	...	...	...	...
823	93159	2012-07-31	2016-03-29	BLK	VALARIS
824	93246	2021-03-22	2024-12-31	GNRC	GENERAC HLDG
825	93422	2010-07-01	2015-06-30	QEP	QEP RESOURCES
826	93429	2017-03-01	2024-12-31	CBOH	CBOE GLO MARKETS
827	93436	2020-12-21	2024-12-31	TSLA	TESLA

828 rows × 5 columns

Pulling in earnings and sell hold buy data from IBES

In [6]:

```
## This currently pulls any ticker I need it to pull from my list where anntims_act
tickers = sp500['ticker'].unique().tolist()
ticker_list = ",".join([f"'{t}'" for t in tickers]) # sql needs a long string comma
```

```
ibes = db.raw_sql(f"""
    SELECT DISTINCT ON (e.ticker, e.fpedats)
    e.ticker,e.cusip, e.oftic, e.meanest, e.actual, e.anndats_act, e.anntims_act, e
    r.numrec, r.buypct, r.sellpct, r.holdpct
    FROM ibes.statsum_epsus e
    LEFT JOIN ibes.recdsum r
    ON e.ticker = r.ticker AND e.statpers = r.statpers
    WHERE e.ticker IN ({ticker_list}) AND e.fpi = '6' AND e.anndats_act >= '{beg_da
    ORDER BY e.ticker, e.fpedats, e.statpers DESC
""", date_cols=['e.anndats_act', 'e.fpe', 'e.statpers'])
```

In [7]:
```
ibes
```

Out[7]:

	ticker	cusip	oftic	meanest	actual	anndats_act	anntims_act	numest	fpi	fp
0	003H	70432V10	PAYC	0.04	0.03	2014-05-16	02:49:00	3.0	6	
1	003H	70432V10	PAYC	0.03	0.04	2014-08-05	16:05:00	5.0	6	
2	003H	70432V10	PAYC	0.04	0.05	2014-11-04	16:05:00	5.0	6	
3	003H	70432V10	PAYC	0.04	0.06	2015-02-10	16:07:00	7.0	6	
4	003H	70432V10	PAYC	0.08	0.12	2015-05-06	16:05:00	8.0	6	
...	...	...	...	...	...	...	...	...	...	
40188	ZY	87254010	TJX	1.11	1.22	2024-02-28	07:30:00	20.0	6	
40189	ZY	87254010	TJX	0.87	0.93	2024-05-22	07:36:00	19.0	6	
40190	ZY	87254010	TJX	0.92	0.96	2024-08-21	07:30:00	18.0	6	
40191	ZY	87254010	TJX	1.09	1.14	2024-11-20	07:30:00	20.0	6	
40192	ZY	87254010	TJX	1.16	1.23	2025-02-26	07:30:00	19.0	6	

40193 rows × 15 columns

Filtering to those that the anndats_act is inside of the band that it was in sp500

In [8]:
```
ibes['anndats_act'] = pd.to_datetime(ibes['anndats_act'])
sp500['start'] = pd.to_datetime(sp500['start'])
sp500['ending'] = pd.to_datetime(sp500['ending'])
```

```python
merged = ibes.merge(sp500, on = 'ticker', how = 'left')

# grabbing the ones where anndats_act is in the sp500 time slot bands
filtered = merged[(merged['anndats_act'] >= merged['start']) &
                  (merged['anndats_act'] <= merged['ending'])]

filtered = filtered.drop(columns = ['oftic', 'fpi', 'fpedats', 'statpers', 'start',
filtered
```

Out[8]:

	ticker	cusip	meanest	actual	anndats_act	anntims_act	numest	numrec	buy
23	003H	70432V10	0.78	0.86	2020-02-05	16:06:00	16.0	17.0	47
24	003H	70432V10	1.27	1.33	2020-04-28	16:16:00	14.0	14.0	42
25	003H	70432V10	0.63	0.62	2020-08-04	16:05:00	12.0	12.0	41
26	003H	70432V10	0.55	0.7	2020-11-04	16:05:00	13.0	13.0	53
27	003H	70432V10	0.79	0.84	2021-02-10	16:05:00	14.0	14.0	64
...	...	...	...	...	...	...	...	...	
41250	ZY	87254010	0.98	1.03	2023-11-15	07:30:00	19.0	24.0	83
41251	ZY	87254010	1.11	1.22	2024-02-28	07:30:00	20.0	25.0	8
41252	ZY	87254010	0.87	0.93	2024-05-22	07:36:00	19.0	25.0	8
41253	ZY	87254010	0.92	0.96	2024-08-21	07:30:00	18.0	25.0	8
41254	ZY	87254010	1.09	1.14	2024-11-20	07:30:00	20.0	25.0	8

29689 rows × 13 columns

Getting valid market dates for sp500 so I can set effective market date based on bmo or amc for announcement time

In [9]:

```python
valid_mkt_dates = db.raw_sql(f"""
SELECT DISTINCT date
FROM crsp.dsf
WHERE date BETWEEN '{beg_datestr}' AND '{end_datestr}'
ORDER BY date;
""")
valid_mkt_dates
```

Out[9]:

	date
0	2010-01-04
1	2010-01-05
2	2010-01-06
3	2010-01-07
4	2010-01-08
...	...
3769	2024-12-24
3770	2024-12-26
3771	2024-12-27
3772	2024-12-30
3773	2024-12-31

3774 rows × 1 columns

In [10]:

```
# making next mkt date
valid_mkt_dates['date'] = pd.to_datetime(valid_mkt_dates['date'])
valid_mkt_dates['tomorrows_date'] = valid_mkt_dates.shift(-1)
valid_mkt_dates = valid_mkt_dates.dropna()
valid_mkt_dates.set_index('date', inplace = True, drop = True)
valid_mkt_dates
```

Out[10]:

	tomorrows_date
date	
2010-01-04	2010-01-05
2010-01-05	2010-01-06
2010-01-06	2010-01-07
2010-01-07	2010-01-08
2010-01-08	2010-01-11
...	...
2024-12-23	2024-12-24
2024-12-24	2024-12-26
2024-12-26	2024-12-27
2024-12-27	2024-12-30
2024-12-30	2024-12-31

3773 rows × 1 columns

In [11]:

```
tomorrows_date_map = valid_mkt_dates['tomorrows_date'].to_dict()
```

Handling cases where the company does not report on a day the market is open. The effective market date for these cases is just the next day the market is open

In [12]:

```
filtered['is_mkt_date'] = filtered['anndats_act'].isin(tomorrows_date_map.keys())
filtered
```

Out[12]:

	ticker	cusip	meanest	actual	anndats_act	anntims_act	numest	numrec	buy
23	003H	70432V10	0.78	0.86	2020-02-05	16:06:00	16.0	17.0	4
24	003H	70432V10	1.27	1.33	2020-04-28	16:16:00	14.0	14.0	4
25	003H	70432V10	0.63	0.62	2020-08-04	16:05:00	12.0	12.0	4
26	003H	70432V10	0.55	0.7	2020-11-04	16:05:00	13.0	13.0	5
27	003H	70432V10	0.79	0.84	2021-02-10	16:05:00	14.0	14.0	6
...	...	...	...	...	...	...	...	...	
41250	ZY	87254010	0.98	1.03	2023-11-15	07:30:00	19.0	24.0	8
41251	ZY	87254010	1.11	1.22	2024-02-28	07:30:00	20.0	25.0	8
41252	ZY	87254010	0.87	0.93	2024-05-22	07:36:00	19.0	25.0	8
41253	ZY	87254010	0.92	0.96	2024-08-21	07:30:00	18.0	25.0	8
41254	ZY	87254010	1.09	1.14	2024-11-20	07:30:00	20.0	25.0	8

29689 rows × 14 columns

In [13]:

```
non_holidays = filtered[filtered['is_mkt_date']].copy()
holidays = filtered[~filtered['is_mkt_date']].copy() # calling it holidays for simp

open_dates = pd.DatetimeIndex(sorted(tomorrows_date_map.keys()))
def get_next_open_date(row_date):
    future_days = open_dates[open_dates>row_date]
    return future_days[0]

holidays.loc[:,'date'] = holidays['anndats_act'].apply(get_next_open_date)
holidays
```

Out[13]:

	ticker	cusip	meanest	actual	anndats_act	anntims_act	numest	numrec	bu
1054	ADM	03948310	0.43	0.45	2012-10-30	12:32:00	2.0	14.0	2
1466	AGN	01849010	1.04	1.06	2012-10-30	09:00:00	25.0	27.0	6
2468	AMBP	74340W10	0.12	0.65	2015-04-19	16:01:00	5.0	21.0	7
2896	AMR	02376R10	-5.88	-5.54	2020-10-18	02:55:00	17.0	19.0	2
3331	APA	03743Q10	1.47	1.29	2022-02-21	17:19:00	22.0	29.0	4
...	...	...	...	...	...	...	...	...	
39610	WMB	96945710	0.49	0.55	2023-02-20	16:15:00	10.0	23.0	6
40036	WUN	95980210	0.45	0.46	2012-10-30	16:00:00	28.0	29.0	5
40295	X	91290910	0.01	0.14	2012-10-30	08:11:00	18.0	22.0	2
40296	X	91290910	0.01	0.14	2012-10-30	08:11:00	18.0	22.0	2
40623	XRAY	24906P10	0.43	0.45	2018-05-06	17:00:00	15.0	16.0	

84 rows × 15 columns

Determining effective date that earnings hits mkt and making that the index. Note that I am going to use a simple cutoff of before 1600 to catch odd edge cases when reported during market hours, but this is extremely rare

In [14]:

```
import numpy as np
from datetime import time

df = non_holidays
df['next_mkt_date'] = df['anndats_act'].map(tomorrows_date_map)
df['anntims_act'] = pd.to_datetime(df['anntims_act'], format='%H:%M:%S').dt.time
mkt_close = time(16, 0, 0)

df['date'] = np.where(df['anntims_act'] < mkt_close, df['anndats_act'], df['next_mk
df
```

Out[14]:

	ticker	cusip	meanest	actual	anndats_act	anntims_act	numest	numrec	buy
23	003H	70432V10	0.78	0.86	2020-02-05	16:06:00	16.0	17.0	47
24	003H	70432V10	1.27	1.33	2020-04-28	16:16:00	14.0	14.0	42
25	003H	70432V10	0.63	0.62	2020-08-04	16:05:00	12.0	12.0	41
26	003H	70432V10	0.55	0.7	2020-11-04	16:05:00	13.0	13.0	53
27	003H	70432V10	0.79	0.84	2021-02-10	16:05:00	14.0	14.0	64
...	...	...	...	...	...	...	...	...	
41250	ZY	87254010	0.98	1.03	2023-11-15	07:30:00	19.0	24.0	83
41251	ZY	87254010	1.11	1.22	2024-02-28	07:30:00	20.0	25.0	8
41252	ZY	87254010	0.87	0.93	2024-05-22	07:36:00	19.0	25.0	8
41253	ZY	87254010	0.92	0.96	2024-08-21	07:30:00	18.0	25.0	8
41254	ZY	87254010	1.09	1.14	2024-11-20	07:30:00	20.0	25.0	8

29605 rows × 16 columns

In [15]:

```
df = df.set_index('date')
df
```

Out[15]:

date	ticker	cusip	meanest	actual	anndats_act	anntims_act	numest	numrec	buy
2020-02-06	003H	70432V10	0.78	0.86	2020-02-05	16:06:00	16.0	17.0	47
2020-04-29	003H	70432V10	1.27	1.33	2020-04-28	16:16:00	14.0	14.0	42
2020-08-05	003H	70432V10	0.63	0.62	2020-08-04	16:05:00	12.0	12.0	41
2020-11-05	003H	70432V10	0.55	0.7	2020-11-04	16:05:00	13.0	13.0	53
2021-02-11	003H	70432V10	0.79	0.84	2021-02-10	16:05:00	14.0	14.0	64
...	...	...	...	...	...	...	...	...	
2023-11-15	ZY	87254010	0.98	1.03	2023-11-15	07:30:00	19.0	24.0	83
2024-02-28	ZY	87254010	1.11	1.22	2024-02-28	07:30:00	20.0	25.0	8
2024-05-22	ZY	87254010	0.87	0.93	2024-05-22	07:36:00	19.0	25.0	8
2024-08-21	ZY	87254010	0.92	0.96	2024-08-21	07:30:00	18.0	25.0	8
2024-11-20	ZY	87254010	1.09	1.14	2024-11-20	07:30:00	20.0	25.0	8

29605 rows × 15 columns

The market closes at 1 on 7/3, 12/24, and Black Friday, so making sure no issues with those dates

In [16]:

```
third_of_july = df[(df['anndats_act'].dt.month == 7)& (df['anndats_act'].dt.day ==
third_of_july
```

Out[16]:

date	ticker	cusip	meanest	actual	anndats_act	anntims_act	numest	numrec	buy
2024-07-03	CDG2	21036P10	3.46	3.57	2024-07-03	07:30:00	14.0	25.0	
2019-07-03	LUK	47233W10	0.24	0.41	2019-07-03	07:00:00	1.0	1.0	1

both are announcing BMO, so assignment of effective mkt date is good

In [17]:
```
xmas_eve =  df[(df['anndats_act'].dt.month == 12)& (df['anndats_act'].dt.day == 24)
xmas_eve
```

Out[17]:

	ticker	cusip	meanest	actual	anndats_act	anntims_act	numest	numrec	buypct
date									

Nobody announced on Christmas Eve, all set

In [18]:
```
black_fridays = black_fridays = [
    pd.Timestamp('2010-11-26'),
    pd.Timestamp('2011-11-25'),
    pd.Timestamp('2012-11-23'),
    pd.Timestamp('2013-11-29'),
    pd.Timestamp('2014-11-28'),
    pd.Timestamp('2015-11-27'),
    pd.Timestamp('2016-11-25'),
    pd.Timestamp('2017-11-24'),
    pd.Timestamp('2018-11-23'),
    pd.Timestamp('2019-11-29'),
    pd.Timestamp('2020-11-27'),
    pd.Timestamp('2021-11-26'),
    pd.Timestamp('2022-11-25'),
    pd.Timestamp('2023-11-24'),
    pd.Timestamp('2024-11-29'),
]

black_friday = df[df['anndats_act'].isin(black_fridays)]
black_friday
```

Out[18]:

	ticker	cusip	meanest	actual	anndats_act	anntims_act	numest	numrec	buypct
date									

Nobody announced on Black Friday, all set

Appending the holidays df to the regular df and removing non common columns

In [19]:
```
df = df.drop(columns = ['next_mkt_date'])
holidays.set_index('date', inplace = True, drop = True)
df = pd.concat([df, holidays], axis=0, ignore_index = False)
df
```

Out[19]:

date	ticker	cusip	meanest	actual	anndats_act	anntims_act	numest	numrec	buy
2020-02-06	003H	70432V10	0.78	0.86	2020-02-05	16:06:00	16.0	17.0	47
2020-04-29	003H	70432V10	1.27	1.33	2020-04-28	16:16:00	14.0	14.0	42
2020-08-05	003H	70432V10	0.63	0.62	2020-08-04	16:05:00	12.0	12.0	41
2020-11-05	003H	70432V10	0.55	0.7	2020-11-04	16:05:00	13.0	13.0	53
2021-02-11	003H	70432V10	0.79	0.84	2021-02-10	16:05:00	14.0	14.0	64
...	...	...	...	...	...	...	...	...	
2023-02-21	WMB	96945710	0.49	0.55	2023-02-20	16:15:00	10.0	23.0	60
2012-10-31	WUN	95980210	0.45	0.46	2012-10-30	16:00:00	28.0	29.0	51
2012-10-31	X	91290910	0.01	0.14	2012-10-30	08:11:00	18.0	22.0	27
2012-10-31	X	91290910	0.01	0.14	2012-10-30	08:11:00	18.0	22.0	27
2018-05-07	XRAY	24906P10	0.43	0.45	2018-05-06	17:00:00	15.0	16.0	6

29689 rows × 14 columns

In [20]:

```
df = df.sort_index()
df
```

Out[20]:

date	ticker	cusip	meanest	actual	anndats_act	anntims_act	numest	numrec	bu
2010-01-06	MONN	61166W10	0.0	-0.02	2010-01-06	08:00:00	17.0	18.0	
2010-01-06	FDO	30700010	0.47	0.49	2010-01-06	07:00:00	20.0	22.0	
2010-01-07	LEN	52605710	-0.47	0.19	2010-01-07	06:00:00	16.0	15.0	
2010-01-07	CDG2	21036P10	0.52	0.54	2010-01-07	07:30:00	8.0	9.0	
2010-01-07	BBBY	07589610	0.42	0.58	2010-01-06	16:15:00	23.0	23.0	
...	...	...	...	...	...	...	...	...	
2024-12-19	DRAM	59511210	1.76	1.79	2024-12-18	16:01:00	24.0	39.0	
2024-12-19	KMX	14313010	0.59	0.81	2024-12-19	06:50:00	12.0	18.0	
2024-12-20	NIKE	65410610	0.65	0.78	2024-12-19	16:15:00	25.0	41.0	
2024-12-20	FDX	31428X10	3.96	4.05	2024-12-19	16:03:00	23.0	33.0	
2024-12-20	CCL	14365830	0.08	0.14	2024-12-20	09:18:00	18.0	27.0	

29689 rows × 14 columns

In [21]:

```
valid_mkt_dates = valid_mkt_dates.reset_index()
valid_mkt_dates['yesterdays_date'] = valid_mkt_dates['date'].shift(1)
valid_mkt_dates = valid_mkt_dates.dropna()
valid_mkt_dates
```

Out[21]:

	date	tomorrows_date	yesterdays_date
1	2010-01-05	2010-01-06	2010-01-04
2	2010-01-06	2010-01-07	2010-01-05
3	2010-01-07	2010-01-08	2010-01-06
4	2010-01-08	2010-01-11	2010-01-07
5	2010-01-11	2010-01-12	2010-01-08
...	...	...	...
3768	2024-12-23	2024-12-24	2024-12-20
3769	2024-12-24	2024-12-26	2024-12-23
3770	2024-12-26	2024-12-27	2024-12-24
3771	2024-12-27	2024-12-30	2024-12-26
3772	2024-12-30	2024-12-31	2024-12-27

3772 rows × 3 columns

In [22]:

```
valid_mkt_dates['t = 1'] = valid_mkt_dates['date'].shift(-1)
valid_mkt_dates['t = 2'] = valid_mkt_dates['date'].shift(-2)
valid_mkt_dates['t = 3'] = valid_mkt_dates['date'].shift(-3)


valid_mkt_dates = valid_mkt_dates.dropna()
valid_mkt_dates.set_index('date', inplace = True, drop = True)
valid_mkt_dates
```

Out[22]:

date	tomorrows_date	yesterdays_date	t = 1	t = 2	t = 3
2010-01-05	2010-01-06	2010-01-04	2010-01-06	2010-01-07	2010-01-08
2010-01-06	2010-01-07	2010-01-05	2010-01-07	2010-01-08	2010-01-11
2010-01-07	2010-01-08	2010-01-06	2010-01-08	2010-01-11	2010-01-12
2010-01-08	2010-01-11	2010-01-07	2010-01-11	2010-01-12	2010-01-13
2010-01-11	2010-01-12	2010-01-08	2010-01-12	2010-01-13	2010-01-14
...	...	...	...	...	...
2024-12-18	2024-12-19	2024-12-17	2024-12-19	2024-12-20	2024-12-23
2024-12-19	2024-12-20	2024-12-18	2024-12-20	2024-12-23	2024-12-24
2024-12-20	2024-12-23	2024-12-19	2024-12-23	2024-12-24	2024-12-26
2024-12-23	2024-12-24	2024-12-20	2024-12-24	2024-12-26	2024-12-27
2024-12-24	2024-12-26	2024-12-23	2024-12-26	2024-12-27	2024-12-30

3769 rows × 5 columns

In [23]:

```
prev_day_map = valid_mkt_dates['yesterdays_date'].to_dict()
t_1_map = valid_mkt_dates['t = 1'].to_dict()
t_2_map = valid_mkt_dates['t = 2'].to_dict()
t_3_map = valid_mkt_dates['t = 3'].to_dict()

df['t = -1'] = df.index.map(prev_day_map)
df['t = 1'] = df.index.map(t_1_map)
df['t = 2'] = df.index.map(t_2_map)
df['t = 3'] = df.index.map(t_3_map)

df
```

Out[23]:

date	ticker	cusip	meanest	actual	anndats_act	anntims_act	numest	numrec	bu
2010-01-06	MONN	61166W10	0.0	-0.02	2010-01-06	08:00:00	17.0	18.0	
2010-01-06	FDO	30700010	0.47	0.49	2010-01-06	07:00:00	20.0	22.0	
2010-01-07	LEN	52605710	-0.47	0.19	2010-01-07	06:00:00	16.0	15.0	
2010-01-07	CDG2	21036P10	0.52	0.54	2010-01-07	07:30:00	8.0	9.0	
2010-01-07	BBBY	07589610	0.42	0.58	2010-01-06	16:15:00	23.0	23.0	
...	...	...	...	...	...	...	...	...	
2024-12-19	DRAM	59511210	1.76	1.79	2024-12-18	16:01:00	24.0	39.0	
2024-12-19	KMX	14313010	0.59	0.81	2024-12-19	06:50:00	12.0	18.0	
2024-12-20	NIKE	65410610	0.65	0.78	2024-12-19	16:15:00	25.0	41.0	
2024-12-20	FDX	31428X10	3.96	4.05	2024-12-19	16:03:00	23.0	33.0	
2024-12-20	CCL	14365830	0.08	0.14	2024-12-20	09:18:00	18.0	27.0	

29689 rows × 18 columns

Grabbing daily open, close, and shares outstanding in thousands for all tickers and adding respective dates and closes to df

In [24]:

```
permnos = tuple(df['permno'].unique().tolist())


price_and_cap_df = db.raw_sql(f"""
SELECT permno, date, prc, openprc, shrout
FROM crsp.dsf
WHERE permno IN {permnos}
  AND date BETWEEN '{beg_datestr}' AND '{end_datestr}'
  AND prc IS NOT NULL
ORDER BY permno, date
"""
, date_cols=['date'])
```

```
price_and_cap_df
```

Out[24]:

	permno	date	prc	openprc	shrout
0	10104	2010-01-04	24.85	24.66	5011220.0
1	10104	2010-01-05	24.82	24.72	5011220.0
2	10104	2010-01-06	24.46	24.77	5011220.0
3	10104	2010-01-07	24.38	24.46	5011220.0
4	10104	2010-01-08	24.68	24.28	5011220.0
...	...	...	...	...	...
432889	93436	2024-12-24	462.28	435.89999	3210060.0
432890	93436	2024-12-26	454.13	465.16	3210060.0
432891	93436	2024-12-27	431.66	449.51999	3210060.0
432892	93436	2024-12-30	417.41	419.39999	3210060.0
432893	93436	2024-12-31	403.84	423.79001	3210060.0

2432894 rows × 5 columns

Adding market cap and splitting based on buckets 1 is mega, 2 is large, 3 is medium. This is just a rough system based on current market distribution of cap types, because raw cutoffs are not accurate due to inflation, growth, and market conditions

In [25]:

```
price_and_cap_df['mkt_cap'] = price_and_cap_df['prc']*price_and_cap_df['shrout']*10
price_and_cap_df= price_and_cap_df.sort_values(by=['date', 'mkt_cap'], ascending=[T
price_and_cap_df['rank_by_date'] = price_and_cap_df.groupby('date').cumcount() + 1

# This is just a rough bucket system for mkt cap based on current spread of mega ca
def assign_bucket(rank):
    if rank <= 50:
        return 1
    elif rank <= 200:
        return 2
    else:
        return 3

price_and_cap_df['bucket'] = price_and_cap_df['rank_by_date'].apply(assign_bucket)
price_and_cap_df
```

Out[25]:

	permno	date	prc	openprc	shrout	mkt_cap	rank_by_da
70369	11850	2010-01-04	69.15	68.72	4731898.0	327210746700.000061	
3774	10107	2010-01-04	30.95	30.62	8811000.0	272700450000.0	
35603	55976	2010-01-04	54.23	53.74	3810172.0	206625627560.0	
272382	14593	2010-01-04	214.00999	213.42999	906282.0	193953401757.179962	
400306	18163	2010-01-04	61.12	61.11	2921734.0	178576382079.999969	
...	...	...	...	...	...	...	
310856	15272	2024-12-31	13.6	13.76	57950.0	788120000.0	58
345161	75573	2024-12-31	22.74	21.85	30118.0	684883320.0	58
215890	29102	2024-12-31	57.17	54.59	8991.0	514015470.0	58
156389	80539	2024-12-31	0.93	0.92	184458.0	171545940.0	58
42985	79089	2024-12-31	1.67	1.78	53194.0	88833980.0	58

2432894 rows × 8 columns

Adding in pricing and mkt cap data from price and cap df

In [26]:

```
df = df.reset_index()

price_df_t_minus_1 = price_and_cap_df.rename(columns={'date': 't = -1', 'prc': 't =
price_df_t_0 = price_and_cap_df.rename(columns={'prc': 't = 0 close'})
price_df_t_1 = price_and_cap_df.rename(columns={'date': 't = 1', 'prc': 't = 1 clos
price_df_t_2 = price_and_cap_df.rename(columns={'date': 't = 2', 'prc': 't = 2 clos
price_df_t_3 = price_and_cap_df.rename(columns={'date': 't = 3', 'prc': 't = 3 clos

df = df.merge(
    price_df_t_minus_1[['permno', 't = -1', 't = -1 close']],
    on=['permno', 't = -1'],
    how='left'
)

df = df.merge(
    price_df_t_0[['permno', 'date', 't = 0 close', 'bucket']],
    on=['permno', 'date'],
```

```
    how='left'
)


df = df.merge(
    price_df_t_1[['permno', 't = 1', 't = 1 close', 't = 1 open']],
    on=['permno', 't = 1'],
    how='left'
)

df = df.merge(
    price_df_t_2[['permno', 't = 2', 't = 2 close', 't = 2 open']],
    on=['permno', 't = 2'],
    how='left'
)

df = df.merge(
    price_df_t_3[['permno', 't = 3', 't = 3 close', 't = 3 open']],
    on=['permno', 't = 3'],
    how='left'
)

df.set_index('date', inplace = True)
df
```

Out[26]:

date	ticker	cusip	meanest	actual	anndats_act	anntims_act	numest	numrec	bu
2010-01-06	MONN	61166W10	0.0	-0.02	2010-01-06	08:00:00	17.0	18.0	
2010-01-06	FDO	30700010	0.47	0.49	2010-01-06	07:00:00	20.0	22.0	
2010-01-07	LEN	52605710	-0.47	0.19	2010-01-07	06:00:00	16.0	15.0	
2010-01-07	CDG2	21036P10	0.52	0.54	2010-01-07	07:30:00	8.0	9.0	
2010-01-07	BBBY	07589610	0.42	0.58	2010-01-06	16:15:00	23.0	23.0	
...	...	...	...	...	...	...	...	...	
2024-12-19	DRAM	59511210	1.76	1.79	2024-12-18	16:01:00	24.0	39.0	
2024-12-19	KMX	14313010	0.59	0.81	2024-12-19	06:50:00	12.0	18.0	
2024-12-20	NIKE	65410610	0.65	0.78	2024-12-19	16:15:00	25.0	41.0	
2024-12-20	FDX	31428X10	3.96	4.05	2024-12-19	16:03:00	23.0	33.0	
2024-12-20	CCL	14365830	0.08	0.14	2024-12-20	09:18:00	18.0	27.0	

29689 rows × 27 columns

Adding returns from (-1, 0), (0, 1 open), (0, 1 close), (0, 2 open), (0, 2 close), (0, 3 open), (0, 3 close)

In [27]:

```
# These are all standard returns not log
df['earnings_reaction_return'] = (df['t = 0 close']/df['t = -1 close'] -1)*100
df['(0, 1 open)_return'] = (df['t = 0 close']/df['t = 1 open'] -1)*100
df['(0, 1 close)_return'] = (df['t = 0 close']/df['t = 1 close'] -1)*100
df['(0, 2 open)_return'] = (df['t = 0 close']/df['t = 2 open'] -1)*100
df['(0, 2 close)_return'] = (df['t = 0 close']/df['t = 2 close'] -1)*100
df['(0, 3 open)_return'] = (df['t = 0 close']/df['t = 3 open'] -1)*100
df['(0, 3 close)_return'] = (df['t = 0 close']/df['t = 3 close'] -1)*100

df
```

Out[27]:

date	ticker	cusip	meanest	actual	anndats_act	anntims_act	numest	numrec	bu
2010-01-06	MONN	61166W10	0.0	-0.02	2010-01-06	08:00:00	17.0	18.0	
2010-01-06	FDO	30700010	0.47	0.49	2010-01-06	07:00:00	20.0	22.0	
2010-01-07	LEN	52605710	-0.47	0.19	2010-01-07	06:00:00	16.0	15.0	
2010-01-07	CDG2	21036P10	0.52	0.54	2010-01-07	07:30:00	8.0	9.0	
2010-01-07	BBBY	07589610	0.42	0.58	2010-01-06	16:15:00	23.0	23.0	
...	...	...	...	...	...	...	...	...	
2024-12-19	DRAM	59511210	1.76	1.79	2024-12-18	16:01:00	24.0	39.0	
2024-12-19	KMX	14313010	0.59	0.81	2024-12-19	06:50:00	12.0	18.0	
2024-12-20	NIKE	65410610	0.65	0.78	2024-12-19	16:15:00	25.0	41.0	
2024-12-20	FDX	31428X10	3.96	4.05	2024-12-19	16:03:00	23.0	33.0	
2024-12-20	CCL	14365830	0.08	0.14	2024-12-20	09:18:00	18.0	27.0	

29689 rows × 34 columns

Adding sector, which is called industry in ibes, I refer to it as industry above as well to remain constent with terminology

In [28]:

```
tickers = tuple(df['ticker'].unique().tolist())

ibes_sector = db.raw_sql(f"""
SELECT n.ticker AS ticker, n.indnam, n.mod_date, n.Cname
FROM tr_ibes_guidance.id_guidance n
JOIN (
    SELECT ticker, MAX(mod_date) as max_mod_date
    FROM tr_ibes_guidance.id_guidance
    WHERE ticker IN {tickers}
    GROUP BY ticker
) t
ON n.ticker = t.ticker AND n.mod_date = t.max_mod_date;
""")
```

```
ibes_sector = ibes_sector.drop(columns = ['mod_date'])
ibes_sector
```

Out[28]:

	ticker	indnam	cname
0	003H	TECHNOLOGY	PAYCOM SOFTWARE INC
1	004W	TECHNOLOGY	ARISTA NETWORKS INC
2	00C6	TECHNOLOGY	KEYSIGHT TECHNOLOGIES INC
3	00WY	TECHNOLOGY	MATCH GROUP INC
4	032M	TECHNOLOGY	VONTIER CORP
...	...	...	...
762	ZBRA	TECHNOLOGY	ZEBRA TECHNOLOGIES CORP
763	ZION	FINANCE	ZIONS BANCORPORATION NA
764	ZMH	HEALTH CARE	ZIMMER BIOMET HOLDINGS INC
765	ZOTS	HEALTH CARE	ZOETIS INC
766	ZY	CONSUMER SERVICES	TJX COMPANIES INC

767 rows × 3 columns

In [29]:

```
len(tickers)
```

Out[29]: 773

mismatch in length so we are missing some

In [30]:

```
original_tickers = set(df['ticker'].unique())
filtered_tickers = set(ibes_sector['ticker'].unique())

missing = original_tickers - filtered_tickers
missing
```

Out[30]:

```
{'02J8',
 '053G',
 'BKHT/1',
 'CEG',
 'CMCS/2',
 'CPGX',
 'CSRAW',
 'DCHA/2',
 'ERIE',
 'FRCA',
 'GEHC',
 'GEV',
 'GOOG/1',
 'KVUE',
 'NFXAV',
 'OGN',
 'SOLV',
 'UARM/1',
 'VLTOW'}
```

In [31]:

```
missing_map = (df[df['ticker'].isin(missing)].drop_duplicates(subset=['ticker', 'cn
missing_map
```

Out[31]:

```
{'BKHT/1': 'BERKSHIRE',
 'DCHA/2': 'DISCOVERY INC',
 'GOOG/1': 'ALPHABET',
 'CPGX': 'COLUMBIA US',
 'CMCS/2': 'COMCAST',
 'CSRAW': 'CSRA',
 'UARM/1': 'UNDER ARMOUR',
 'FRCA': 'FRST REP BK',
 'NFXAV': 'FOX',
 '02J8': 'AMCR',
 'OGN': 'ORGANON',
 'CEG': 'CONSTELLATION PA',
 'GEHC': 'GE HEALTHCARE',
 'VLTOW': 'VERALTO',
 'KVUE': 'KENVUE',
 'GEV': 'GE VERNOVA',
 'SOLV': 'SOLVENTUM',
 '053G': 'SMURFIT WESTROCK',
 'ERIE': 'ERIE INDEMNITY'}
```

It looks like the bulk of the issue is coming from companies with spinoffs or multiple classes of shares.

I do not want class a and class b shares overweighting single occurrences, so they will be removed from the dataset, but the spinoffs will stay

In [32]:

```
to_remove = {'BKHT/1', 'DCHA/2', 'GOOG/1', 'CMCS/2', 'UARM/1', 'NFXAV'}
missing_df = pd.DataFrame(list(missing_map.items()), columns = ['ticker', 'cname'])
missing_df = missing_df[~missing_df['ticker'].isin(to_remove)]
```

```python
df = df[~df['ticker'].isin(to_remove)]
missing_df
```

Out[32]:

	ticker	cname
3	CPGX	COLUMBIA US
5	CSRAW	CSRA
7	FRCA	FRST REP BK
9	02J8	AMCR
10	OGN	ORGANON
11	CEG	CONSTELLATION PA
12	GEHC	GE HEALTHCARE
13	VLTOW	VERALTO
14	KVUE	KENVUE
15	GEV	GE VERNOVA
16	SOLV	SOLVENTUM
17	053G	SMURFIT WESTROCK
18	ERIE	ERIE INDEMNITY

Adding in the respective indnam of each ticker that should remain

In [33]:

```python
ibes_sector['indnam'].unique()
```

Out[33]:

```
<StringArray>
[          'TECHNOLOGY',          'CAPITAL GOODS',      'CONSUMER SERVICES',
          'HEALTH CARE', 'CONSUMER NON-DURABLES',                'FINANCE',
               'ENERGY',       'PUBLIC UTILITIES',      'BASIC INDUSTRIES',
       'TRANSPORTATION',      'CONSUMER DURABLES']
Length: 11, dtype: string
```

In [34]:

```python
missing_df['indnam'] = [
    "FINANCE",               # CPGX
    "TECHNOLOGY",            # CSRAW
    "FINANCE",               # FRCA
    "BASIC INDUSTRIES",      # 02J8 (Amcor)
    "HEALTH CARE",           # OGN
    "PUBLIC UTILITIES",      # CEG
    "HEALTH CARE",           # GEHC
    "CAPITAL GOODS",         # VLTOW
    "CONSUMER NON-DURABLES", # KVUE
    "CAPITAL GOODS",         # GEV
    "HEALTH CARE",           # SOLV
    "BASIC INDUSTRIES",      # 053G
    "FINANCE"                # ERIE
```

```
]
missing_df
```

Out[34]:

	ticker	cname	indnam
3	CPGX	COLUMBIA US	FINANCE
5	CSRAW	CSRA	TECHNOLOGY
7	FRCA	FRST REP BK	FINANCE
9	02J8	AMCR	BASIC INDUSTRIES
10	OGN	ORGANON	HEALTH CARE
11	CEG	CONSTELLATION PA	PUBLIC UTILITIES
12	GEHC	GE HEALTHCARE	HEALTH CARE
13	VLTOW	VERALTO	CAPITAL GOODS
14	KVUE	KENVUE	CONSUMER NON-DURABLES
15	GEV	GE VERNOVA	CAPITAL GOODS
16	SOLV	SOLVENTUM	HEALTH CARE
17	053G	SMURFIT WESTROCK	BASIC INDUSTRIES
18	ERIE	ERIE INDEMNITY	FINANCE

In [35]:

```
ibes_sector = pd.concat([ibes_sector, missing_df], axis = 0, ignore_index = True)
ibes_sector
```

Out[35]:

	ticker	indnam	cname
0	003H	TECHNOLOGY	PAYCOM SOFTWARE INC
1	004W	TECHNOLOGY	ARISTA NETWORKS INC
2	00C6	TECHNOLOGY	KEYSIGHT TECHNOLOGIES INC
3	00WY	TECHNOLOGY	MATCH GROUP INC
4	032M	TECHNOLOGY	VONTIER CORP
...	...	...	...
775	KVUE	CONSUMER NON-DURABLES	KENVUE
776	GEV	CAPITAL GOODS	GE VERNOVA
777	SOLV	HEALTH CARE	SOLVENTUM
778	053G	BASIC INDUSTRIES	SMURFIT WESTROCK
779	ERIE	FINANCE	ERIE INDEMNITY

780 rows × 3 columns

In [36]:
```
len(df['ticker'].unique().tolist())
```

Out[36]: 767

In [37]:
```
len(ibes_sector['ticker'].unique().tolist())
```

Out[37]: 767

In [38]:
```
duplicates = ibes_sector[ibes_sector['ticker'].duplicated(keep=False)]
duplicates
```

Out[38]:

	ticker	indnam	cname
126	CDAY	TECHNOLOGY	CERIDIAN HCM HOLDING INC
127	CDAY	TECHNOLOGY	DAYFORCE INC
173	CSC	TECHNOLOGY	DXC TECHNOLOGY COMAPNY
174	CSC	TECHNOLOGY	DXC TECHNOLOGY CO
247	ERI	CONSUMER SERVICES	ELDORADO RESORTS INC
248	ERI	CONSUMER SERVICES	CAESARS ENTERTAINMENT INC
264	FBHS	CAPITAL GOODS	FORTUNE BRANDS HOME & SECURITY I
265	FBHS	CAPITAL GOODS	FORTUNE BRANDS INNOVATIONS INC
300	GDI	CAPITAL GOODS	INGERSOLL RAND INC
301	GDI	CAPITAL GOODS	INGERSOLL RAND INC
386	KAN	PUBLIC UTILITIES	WESTAR ENERGY INC
387	KAN	PUBLIC UTILITIES	EVERGY INC
435	MCD	CONSUMER SERVICES	MCDONALD'S CORP
436	MCD	CONSUMER SERVICES	MCDONALD'S CORP
470	MSFT	TECHNOLOGY	MICROSOFT CORPT
471	MSFT	TECHNOLOGY	MICROSOFT CORP
496	NOI	ENERGY	NOV INC
497	NOI	ENERGY	NOV INC
622	SJM	CONSUMER NON-DURABLES	SMUCKER J M CO
623	SJM	CONSUMER NON-DURABLES	J M SMUCKER CO
656	SYMC	TECHNOLOGY	NORTONLIFELOCK INC
657	SYMC	TECHNOLOGY	GEN DIGITAL INC
729	WATS	HEALTH CARE	ACTAVIS PLC
730	WATS	HEALTH CARE	ALLERGAN PLC
751	XL	FINANCE	XL GROUP LTD
752	XL	FINANCE	XL GROUP LTD

Nothing in there that needs to be kept so picking 1

In [39]:

```
ibes_sector = ibes_sector.drop(columns = ['cname'])
ibes_sector
```

Out[39]:

	ticker	indnam
0	003H	TECHNOLOGY
1	004W	TECHNOLOGY
2	00C6	TECHNOLOGY
3	00WY	TECHNOLOGY
4	032M	TECHNOLOGY
...	...	...
775	KVUE	CONSUMER NON-DURABLES
776	GEV	CAPITAL GOODS
777	SOLV	HEALTH CARE
778	053G	BASIC INDUSTRIES
779	ERIE	FINANCE

780 rows × 2 columns

In [40]:
```
ibes_sector = ibes_sector.drop_duplicates(subset='ticker').reset_index(drop=True)
ibes_sector
```

Out[40]:

	ticker	indnam
0	003H	TECHNOLOGY
1	004W	TECHNOLOGY
2	00C6	TECHNOLOGY
3	00WY	TECHNOLOGY
4	032M	TECHNOLOGY
...	...	...
762	KVUE	CONSUMER NON-DURABLES
763	GEV	CAPITAL GOODS
764	SOLV	HEALTH CARE
765	053G	BASIC INDUSTRIES
766	ERIE	FINANCE

767 rows × 2 columns

In [41]:
```
ibes_sector = ibes_sector.set_index('ticker')
sector_map = ibes_sector['indnam'].to_dict()
df = df.copy()
```

```
df.loc[:,'Industry'] = df['ticker'].map(sector_map)
df
```

Out[41]:

date	ticker	cusip	meanest	actual	anndats_act	anntims_act	numest	numrec	bu
2010-01-06	MONN	61166W10	0.0	-0.02	2010-01-06	08:00:00	17.0	18.0	
2010-01-06	FDO	30700010	0.47	0.49	2010-01-06	07:00:00	20.0	22.0	
2010-01-07	LEN	52605710	-0.47	0.19	2010-01-07	06:00:00	16.0	15.0	
2010-01-07	CDG2	21036P10	0.52	0.54	2010-01-07	07:30:00	8.0	9.0	
2010-01-07	BBBY	07589610	0.42	0.58	2010-01-06	16:15:00	23.0	23.0	
...	...	...	...	...	...	...	...	...	
2024-12-19	DRAM	59511210	1.76	1.79	2024-12-18	16:01:00	24.0	39.0	
2024-12-19	KMX	14313010	0.59	0.81	2024-12-19	06:50:00	12.0	18.0	
2024-12-20	NIKE	65410610	0.65	0.78	2024-12-19	16:15:00	25.0	41.0	
2024-12-20	FDX	31428X10	3.96	4.05	2024-12-19	16:03:00	23.0	33.0	
2024-12-20	CCL	14365830	0.08	0.14	2024-12-20	09:18:00	18.0	27.0	

29518 rows × 35 columns

END OF DATA PULLING

Checking to see how much of the universe is lost by limiting universe to 3 or more analyst estimates and recommendations

In [42]:

```
df[(df['numest']<3) | (df['numrec'] <3)]
```

Out[42]:

date	ticker	cusip	meanest	actual	anndats_act	anntims_act	numest	numrec	bu
2010-01-27	BXP	10112110	0.35	0.38	2010-01-26	18:40:00	2.0	18.0	
2010-01-29	CPWR	20563810	0.1	0.11	2010-01-28	16:13:00	2.0	2.0	1
2010-02-04	KIM	49446R10	0.05	0.11	2010-02-03	17:03:00	2.0	21.0	2
2010-02-18	UEP	02360810	0.05	0.37	2010-02-18	08:05:00	1.0	5.0	
2010-02-23	VNO	92904210	0.23	-0.84	2010-02-23	09:03:00	1.0	9.0	2
...	...	...	...	...	...	...	...	...	
2024-08-08	VSTE	92840M10	0.98	0.9	2024-08-08	07:00:00	2.0	12.0	9
2024-08-08	NRGE	62937750	1.59	3.37	2024-08-08	06:56:00	2.0	10.0	
2024-10-25	VRSN	92343E10	2.01	2.07	2024-10-24	16:08:00	2.0	4.0	
2024-11-01	ERIE	29530P10	3.02	3.06	2024-10-31	16:22:00	2.0	2.0	
2024-11-08	NRGE	62937750	2.05	1.9	2024-11-08	07:07:00	2.0	11.0	4

193 rows × 35 columns

Restricting universe to cases where there is three or more estimates and 3 or more recommendations. Doing this gives more credit to the estimates and recommendations since there are more opinions involved

In [43]:

```
df = df[(df['numest']>=3) & (df['numrec'] >=3)]
df
```

Out[43]:

date	ticker	cusip	meanest	actual	anndats_act	anntims_act	numest	numrec	bu
2010-01-06	MONN	61166W10	0.0	-0.02	2010-01-06	08:00:00	17.0	18.0	
2010-01-06	FDO	30700010	0.47	0.49	2010-01-06	07:00:00	20.0	22.0	
2010-01-07	LEN	52605710	-0.47	0.19	2010-01-07	06:00:00	16.0	15.0	
2010-01-07	CDG2	21036P10	0.52	0.54	2010-01-07	07:30:00	8.0	9.0	
2010-01-07	BBBY	07589610	0.42	0.58	2010-01-06	16:15:00	23.0	23.0	
...	...	...	...	...	...	...	...	...	
2024-12-19	DRAM	59511210	1.76	1.79	2024-12-18	16:01:00	24.0	39.0	
2024-12-19	KMX	14313010	0.59	0.81	2024-12-19	06:50:00	12.0	18.0	
2024-12-20	NIKE	65410610	0.65	0.78	2024-12-19	16:15:00	25.0	41.0	
2024-12-20	FDX	31428X10	3.96	4.05	2024-12-19	16:03:00	23.0	33.0	
2024-12-20	CCL	14365830	0.08	0.14	2024-12-20	09:18:00	18.0	27.0	

29324 rows × 35 columns

Analyzing missing values and replacing or removing where appropriate

In [44]:

```
df.isna().sum()
```

Out[44]:

```
ticker                      0
cusip                       0
meanest                     0
actual                      3
anndats_act                 0
anntims_act                 0
numest                      0
numrec                      0
buypct                      0
sellpct                     0
holdpct                     0
permno                      0
cname                       0
is_mkt_date                 0
t = -1                      0
t = 1                       0
t = 2                       0
t = 3                       0
t = -1 close                0
t = 0 close                 1
bucket                      1
t = 1 close                 1
t = 1 open                  1
t = 2 close                 4
t = 2 open                  4
t = 3 close                 5
t = 3 open                  5
earnings_reaction_return    1
(0, 1 open)_return          1
(0, 1 close)_return         1
(0, 2 open)_return          4
(0, 2 close)_return         4
(0, 3 open)_return          5
(0, 3 close)_return         5
Industry                    0
dtype: int64
```

Looking at missing actuals

In [45]:

```
df[df['actual'].isna()].drop(columns = ['anntims_act', 'Industry'])
```

Out[45]:

date	ticker	cusip	meanest	actual	anndats_act	numest	numrec	buypct	sellpct
2013-01-23	ABBV	00287Y10	0.99	<NA>	2013-01-23	7.0	10.0	50.0	0.0
2020-05-07	WATS	G0177J10	3.94	<NA>	2020-05-07	6.0	17.0	11.76	0.0
2024-05-03	PDP	72378710	4.87	<NA>	2024-05-02	18.0	25.0	16.0	4.0

3 rows × 33 columns

ALLERGAN was bought by Abbvie on May 8 2020 DROP

Pioneer merged with Exon on the day they were supposed to announce earnings DROP

ABBV is just missing the data. Here is a screenshot from another provider:

	2013-01-23
ticker	ABBV
actual_eps	1.0
estimated_eps	0.99
actual_revenue	4508000000
estimated_revenue	NaN

Inputing actual for ABBV and removing WATS and PDP by just calling to remove those missing actuals

In [46]:

```
df.loc[(df.index == '2013-01-23') & (df['ticker'] == 'ABBV'), 'actual'] = 1.0
df.loc[(df.index == '2013-01-23') & (df['ticker'] == 'ABBV')]
```

Out[46]:

date	ticker	cusip	meanest	actual	anndats_act	anntims_act	numest	numrec	buy
2013-01-23	ABBV	00287Y10	0.99	1.0	2013-01-23	07:47:00	7.0	10.0	5

1 rows × 35 columns

In [47]:

```
df[df['actual'].isna()].drop(columns = ['anntims_act', 'Industry'])
```

Out[47]:

date	ticker	cusip	meanest	actual	anndats_act	numest	numrec	buypct	sellpct	l
2020-05-07	WATS	G0177J10	3.94	<NA>	2020-05-07	6.0	17.0	11.76	0.0	
2024-05-03	PDP	72378710	4.87	<NA>	2024-05-02	18.0	25.0	16.0	4.0	

2 rows × 33 columns

In [48]:

```
df = df[~df['actual'].isna()]
df.isna().sum()
```

```
Out[48]: ticker                      0
         cusip                       0
         meanest                     0
         actual                      0
         anndats_act                 0
         anntims_act                 0
         numest                      0
         numrec                      0
         buypct                      0
         sellpct                     0
         holdpct                     0
         permno                      0
         cname                       0
         is_mkt_date                 0
         t = -1                      0
         t = 1                       0
         t = 2                       0
         t = 3                       0
         t = -1 close                0
         t = 0 close                 0
         bucket                      0
         t = 1 close                 0
         t = 1 open                  0
         t = 2 close                 2
         t = 2 open                  2
         t = 3 close                 3
         t = 3 open                  3
         earnings_reaction_return    0
         (0, 1 open)_return          0
         (0, 1 close)_return         0
         (0, 2 open)_return          2
         (0, 2 close)_return         2
         (0, 3 open)_return          3
         (0, 3 close)_return         3
         Industry                    0
         dtype: int64
```

Looking at t = 3 close to see issues since 3 has the most and most likely overlap for first 2

```
In [49]: df[df['t = 3 close'].isna()]['cname']
```

```
Out[49]: date
         2011-02-24    ALLEGHENY ENERGY
         2015-01-22            COVIDIEN
         2015-07-02    FAMILY DOLLAR ST
         Name: cname, dtype: object
```

Alegheny merged with FirstEnergy corp on feb 25 2011, so it will be dropped. People already knew about this event ahead of time, so no reason to trade it

Medtronic bought Covidien on jan 26 so not considered, news of this was known ahead of time

Dollar Tree bought out Family dollar on july 6, again not considered and this was already known ahead of time

Given that all three missing pricing data is the result of mergers and buyouts, none of them will be considered, as this was known ahead of time

In [50]:
```python
df = df[~df['t = 3 close'].isna()]
df.isna().sum()
```

Out[50]:
```
ticker                     0
cusip                      0
meanest                    0
actual                     0
anndats_act                0
anntims_act                0
numest                     0
numrec                     0
buypct                     0
sellpct                    0
holdpct                    0
permno                     0
cname                      0
is_mkt_date                0
t = -1                     0
t = 1                      0
t = 2                      0
t = 3                      0
t = -1 close               0
t = 0 close                0
bucket                     0
t = 1 close                0
t = 1 open                 0
t = 2 close                0
t = 2 open                 0
t = 3 close                0
t = 3 open                 0
earnings_reaction_return   0
(0, 1 open)_return         0
(0, 1 close)_return        0
(0, 2 open)_return         0
(0, 2 close)_return        0
(0, 3 open)_return         0
(0, 3 close)_return        0
Industry                   0
dtype: int64
```

In [51]:
```python
df
```

Out[51]:

	ticker	cusip	meanest	actual	anndats_act	anntims_act	numest	numrec	bu
date									
2010-01-06	MONN	61166W10	0.0	-0.02	2010-01-06	08:00:00	17.0	18.0	
2010-01-06	FDO	30700010	0.47	0.49	2010-01-06	07:00:00	20.0	22.0	
2010-01-07	LEN	52605710	-0.47	0.19	2010-01-07	06:00:00	16.0	15.0	
2010-01-07	CDG2	21036P10	0.52	0.54	2010-01-07	07:30:00	8.0	9.0	
2010-01-07	BBBY	07589610	0.42	0.58	2010-01-06	16:15:00	23.0	23.0	
...	...	...	...	...	...	...	...	...	
2024-12-19	DRAM	59511210	1.76	1.79	2024-12-18	16:01:00	24.0	39.0	
2024-12-19	KMX	14313010	0.59	0.81	2024-12-19	06:50:00	12.0	18.0	
2024-12-20	NIKE	65410610	0.65	0.78	2024-12-19	16:15:00	25.0	41.0	
2024-12-20	FDX	31428X10	3.96	4.05	2024-12-19	16:03:00	23.0	33.0	
2024-12-20	CCL	14365830	0.08	0.14	2024-12-20	09:18:00	18.0	27.0	

29319 rows × 35 columns

In [52]:

```
df = df.drop(columns = ['(0, 1 open)_return',
 '(0, 2 close)_return',
 '(0, 2 open)_return',
 '(0, 3 close)_return',
 '(0, 3 open)_return',
 'anndats_act',
 'anntims_act',
 'cname',
 'is_mkt_date',
 't = -1',
 't = -1 close',
 't = 0 close',
 't = 1',
 't = 1 close',
 't = 1 open',
 't = 2',
 't = 2 close',
```

```
 't = 2 open',
 't = 3',
 't = 3 close',
 't = 3 open'])
```

Performing data preproccessing

In [54]:
```
df['beat_earnings'] = ((df['actual'] - df['meanest']) > 0).astype(int)
df = df.drop(columns = ['actual', 'meanest', 'holdpct']) # holdpct is redundent sin
df
```

Out[54]:

	ticker	cusip	numest	numrec	buypct	sellpct	permno	mkt_cap_bin	earnin
date									
2010-01-06	MONN	61166W10	17.0	18.0	38.89	11.11	88668	1.0	
2010-01-06	FDO	30700010	20.0	22.0	40.91	4.55	53866	3.0	
2010-01-07	LEN	52605710	16.0	15.0	46.67	6.67	52708	3.0	
2010-01-07	CDG2	21036P10	8.0	9.0	22.22	33.33	69796	3.0	
2010-01-07	BBBY	07589610	23.0	23.0	34.78	4.35	77659	3.0	
...	...	...	...	...	...	...	...	...	
2024-12-19	DRAM	59511210	24.0	39.0	87.18	2.56	53613	2.0	
2024-12-19	KMX	14313010	12.0	18.0	50.0	16.67	89508	3.0	
2024-12-20	NIKE	65410610	25.0	41.0	48.78	4.88	57665	2.0	
2024-12-20	FDX	31428X10	23.0	33.0	69.7	6.06	60628	2.0	
2024-12-20	CCL	14365830	18.0	27.0	77.78	11.11	75154	3.0	

29319 rows × 12 columns

In [55]:
```
df = pd.get_dummies(df, columns=['Industry', 'mkt_cap_bin'], dtype = int)
df
```

Out[55]:

date	ticker	cusip	numest	numrec	buypct	sellpct	permno	earnings_reaction_ret
2010-01-06	MONN	61166W10	17.0	18.0	38.89	11.11	88668	1.172
2010-01-06	FDO	30700010	20.0	22.0	40.91	4.55	53866	12.477
2010-01-07	LEN	52605710	16.0	15.0	46.67	6.67	52708	12.846
2010-01-07	CDG2	21036P10	8.0	9.0	22.22	33.33	69796	-0.99
2010-01-07	BBBY	07589610	23.0	23.0	34.78	4.35	77659	6.907
...	...	...	...	...	...	...	...	
2024-12-19	DRAM	59511210	24.0	39.0	87.18	2.56	53613	-16.179
2024-12-19	KMX	14313010	12.0	18.0	50.0	16.67	89508	3.45
2024-12-20	NIKE	65410610	25.0	41.0	48.78	4.88	57665	-0.207
2024-12-20	FDX	31428X10	23.0	33.0	69.7	6.06	60628	-0.054
2024-12-20	CCL	14365830	18.0	27.0	77.78	11.11	75154	6.433

29319 rows × 24 columns

In [56]:

```
df_numerical = df.drop(columns = ['ticker', 'cusip', 'permno'])
df_numerical
```

Out[56]:

date	numest	numrec	buypct	sellpct	earnings_reaction_return	(0, 1 close)_return	beat_earni
2010-01-06	17.0	18.0	38.89	11.11	1.172745	0.360633	
2010-01-06	20.0	22.0	40.91	4.55	12.477264	1.277432	
2010-01-07	16.0	15.0	46.67	6.67	12.846715	-3.0721	
2010-01-07	8.0	9.0	22.22	33.33	-0.99194	1.979566	
2010-01-07	23.0	23.0	34.78	4.35	6.907979	-0.214133	
...	...	...	...	...	...	...	
2024-12-19	24.0	39.0	87.18	2.56	-16.179018	-3.362184	
2024-12-19	12.0	18.0	50.0	16.67	3.45124	-0.047466	
2024-12-20	25.0	41.0	48.78	4.88	-0.207523	0.234497	
2024-12-20	23.0	33.0	69.7	6.06	-0.054368	2.498048	
2024-12-20	18.0	27.0	77.78	11.11	6.433678	4.15857	

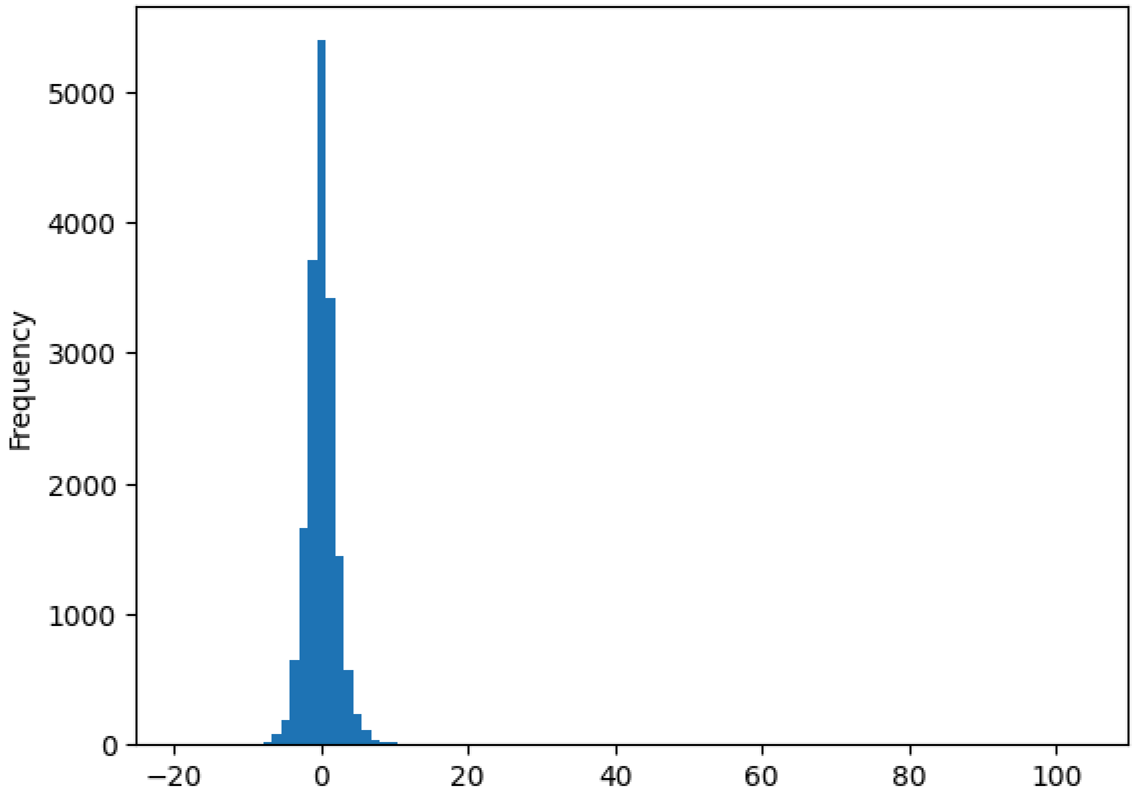
29319 rows × 21 columns

Creating three buckets for returns of entire df based on returns of the 33rd, and 66th percentiles from the training data

In [57]:

```
training = df[df.index < '2019-01-01']
training['(0, 1 close)_return'].plot(kind = 'hist', bins = 100)

percentiles = np.percentile(training['(0, 1 close)_return'], [33,66])
print(percentiles)
```

```
[-0.69538085  0.63824767]
```



Setting up bins for entire data set based on training set, so if return > .63 then long, the middle is flat, and return < -.69 short

In [58]:
```
# Assign target classes for entire dataset
def classify_return(x, percentiles):
    if x < percentiles[0]:
        return 0  # short
    elif x > percentiles[1]:
        return 2  # long
    else:
        return 1  # middle / flat

df_numerical['target_class'] = df_numerical['(0, 1 close)_return'].apply(lambda x:
df_numerical = df_numerical.drop(columns = ['(0, 1 close)_return'])
df_numerical
```

Out[58]:

date	numest	numrec	buypct	sellpct	earnings_reaction_return	beat_earnings	Industry_ INDUS
2010-01-06	17.0	18.0	38.89	11.11	1.172745	0	
2010-01-06	20.0	22.0	40.91	4.55	12.477264	1	
2010-01-07	16.0	15.0	46.67	6.67	12.846715	1	
2010-01-07	8.0	9.0	22.22	33.33	-0.99194	1	
2010-01-07	23.0	23.0	34.78	4.35	6.907979	1	
...	...	...	...	...	...	...	
2024-12-19	24.0	39.0	87.18	2.56	-16.179018	1	
2024-12-19	12.0	18.0	50.0	16.67	3.45124	1	
2024-12-20	25.0	41.0	48.78	4.88	-0.207523	1	
2024-12-20	23.0	33.0	69.7	6.06	-0.054368	1	
2024-12-20	18.0	27.0	77.78	11.11	6.433678	1	

29319 rows × 21 columns

Brief Summary of features and predictor variable

FEATURES

- numest: Number of analysts estimating earnings
- numrec: Number of analysts giving a recommendation for the stock strong buy, buy, hold, sell, strong sell
- earnings_reaction_return: The close to close return of the stock on the day the market reacted to earnings
- Industries are self explanatory
- mkt_cap_bin_1.0: Is 1 if the stock was in the top 50 stocks in sp500 weighted by mkt cap that day
- mkt_cap_bin_2.0: is the next 50 to 200 stocks

- mkt_cap_bin_3.0 is the remaining stocks
- beat earnings: 1 if mean earnings estimate >= actual earnings estimate and 0 otherwise
- buypct: The percent of analysts that rated the stock a buy or strong buy
- sellpct: Same thing for sell or strong sell

TARGET:

- 0 means the return from the close when the market reacted to earnings to the next days close is < .69%, which was the 33rd percentile of returns from the training set. I call this shorts
- 2 means the return from the close when the market reacted to earnings to the next days close is > .63%, which was the 66th percentile of returns from the training set. I call this longs
- 1 means return is between shorts and longs. I call this flats

GradientBoostingClassifier modeling

In [66]:
```
from sklearn.ensemble import GradientBoostingClassifier
from sklearn.metrics import classification_report, confusion_matrix



train = df_numerical[df_numerical.index <'2019-01-01']
test = df_numerical[df_numerical.index >='2019-01-01']

X_train = train.drop(columns = ['target_class'])
y_train = train['target_class']

X_test = test.drop(columns = ['target_class'])
y_test = test['target_class']


gbc = GradientBoostingClassifier(
    n_estimators=200,
    learning_rate=0.05,
    max_depth=3,
    random_state=42
)

gbc.fit(X_train, y_train)

y_pred = gbc.predict(X_test)


print(classification_report(y_test, y_pred))
conf_m = confusion_matrix(y_test, y_pred)
confusion_mat = pd.DataFrame(conf_m, index = ['actual short', 'actual flat', 'actua
confusion_mat
```

```
              precision    recall  f1-score   support

           0       0.39      0.25      0.31      4322
           1       0.31      0.42      0.35      3150
           2       0.37      0.41      0.39      4253

    accuracy                           0.35     11725
   macro avg       0.36      0.36      0.35     11725
weighted avg       0.36      0.35      0.35     11725
```

Out[66]:

	predicted short	predicted flat	predicted long
actual short	1075	1467	1780
actual flat	649	1323	1178
actual long	1001	1522	1730

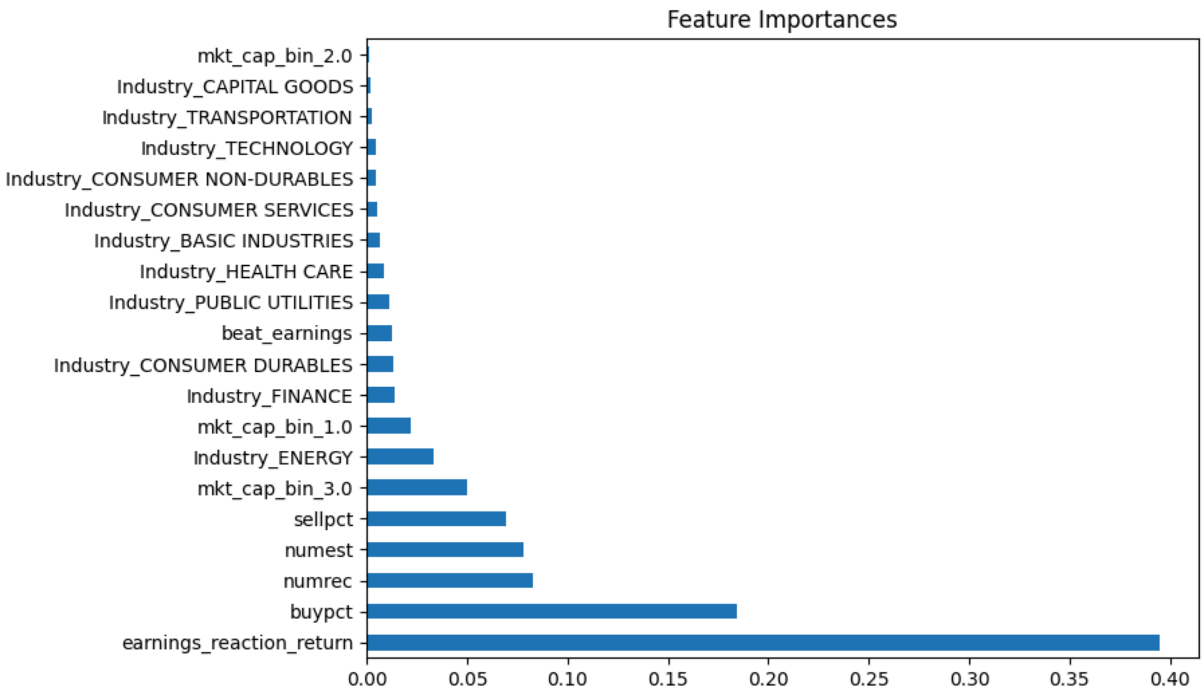
The models overall accuracy is .35, which is slightly above just guessing uniformly. We can see from the confusion matrix that there are lots of long to short and short to long prediction errors. This is not good because it means that we are not seperating the two classes properly, and that if one was to employ this strategy they would be taking the wrong position far to frequently.

A future solution for the application of a trading strategy could be to force the model during training to put observations that it is unsure of into the flat class, and overpenalize the case when the model predicts long and the actual is short or predicts short and the actual is long. This could be done through a custom loss function in XGBoost. This way while our overall accuracy may decrease due to 'punting' unsure ones into the flat class, the accuracy of predicting longs and shorts increases and our strategy can become more reliable.

Here is the feature importances that our tree classifier has decided on.

In [60]:

```python
import pandas as pd
import matplotlib.pyplot as plt

# Feature importances
importances = pd.Series(gbc.feature_importances_, index=X_train.columns)
importances.sort_values(ascending=False).plot(kind='barh', figsize=(8,6))
plt.title("Feature Importances")
plt.show()
```



We can see that the model weights earnings reaction return the highest, followed by analyst level items, then being a small cap, energy,then everything else becomes less and less relevant

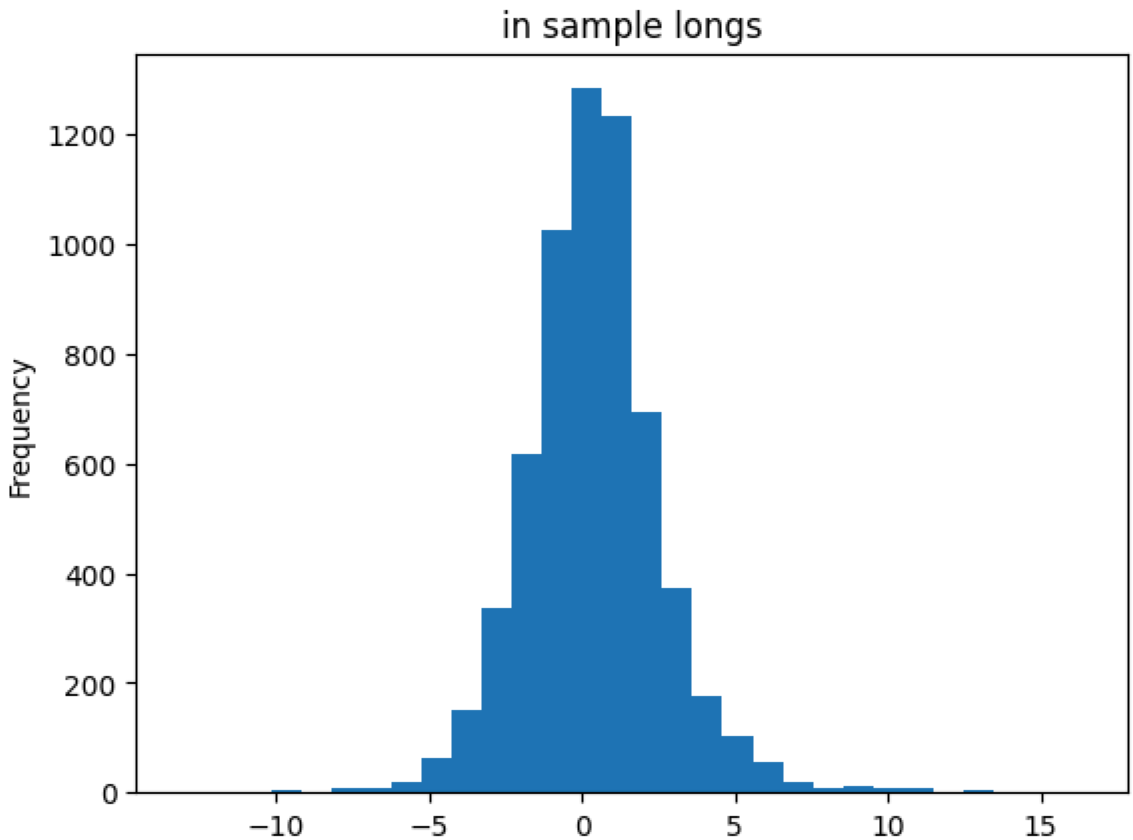
Something of interest may be the fact that numest is of more importance than whether or not the company beat earnings. This makes intuitive sense because the more guesses they are the more likely the average of the guesses is correct, so the more estimators the better. This could also be attributed to numrec and numest being fairly close at most times.

The distribution of returns of the in sample strategy

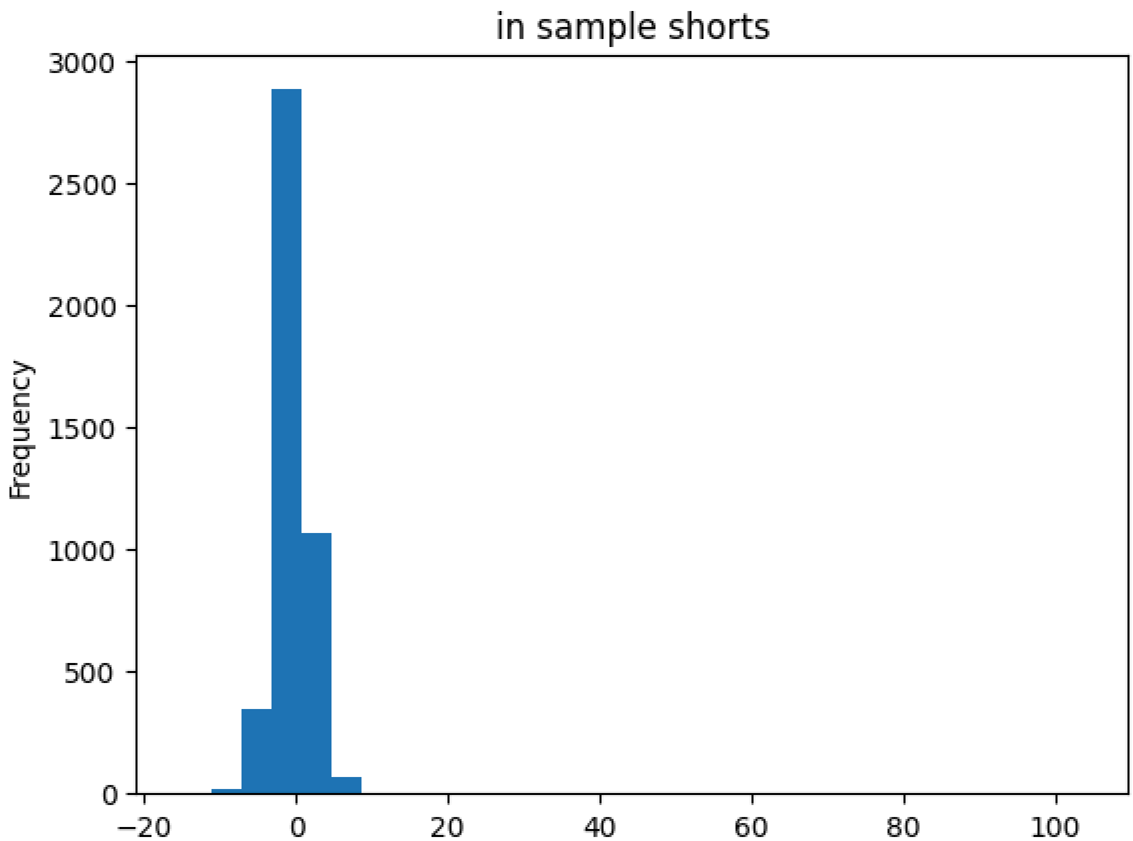
In [61]:

```
y_output = gbc.predict(X_train)
in_sample_long_form = df[df.index <'2019-01-01']
in_sample_long_form['model_prediction'] = y_output

in_longs = in_sample_long_form[in_sample_long_form['model_prediction'] == 2]
in_shorts = in_sample_long_form[in_sample_long_form['model_prediction'] == 0]

in_longs['(0, 1 close)_return'].plot(kind = 'hist', bins = 30, title = "in sample l
plt.show()
display(in_longs['(0, 1 close)_return'].describe())
in_shorts['(0, 1 close)_return'].plot(kind = 'hist', bins = 30, title = "in sample 
display(plt.show())
in_shorts['(0, 1 close)_return'].describe()
```

```
/tmp/33173679.1.jupyterhub.q/ipykernel_2154085/2685676333.py:3: SettingWithCopyWarni
ng:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/u
ser_guide/indexing.html#returning-a-view-versus-a-copy
  in_sample_long_form['model_prediction'] = y_output
```




```
count       6213.0
mean      0.370054
std       2.260899
min     -13.103448
25%       -0.95457
50%       0.328176
75%       1.555847
max      16.397229
Name: (0, 1 close)_return, dtype: Float64
```




```
None
```

Out[61]:

```
count        4391.0
mean      -0.362808
std        2.743014
min      -15.072579
25%       -1.658398
50%       -0.408163
75%        0.832688
max      103.719547
Name: (0, 1 close)_return, dtype: Float64
```

In training we can see that there is some directional bias in the means for both toward our position, but this is very low, especially relative to the deviation of returns. Not to mention it is most likely completely overfiting.

Also, note the outlair at 100, this is in sample training too. In a future project when I have some more knowledge about how the loss function works, I would like to build one that overpenalizes being wrong between longs and shorts and whenever the model is unsure it punts the classification into the flat slot

In [62]:

```
out_of_sample_long_form = df[df.index >='2019-01-01']
out_of_sample_long_form['model_prediction'] = y_pred
out_of_sample_long_form
```

```
/tmp/33173679.1.jupyterhub.q/ipykernel_2154085/793002830.py:2: SettingWithCopyWarnin
g:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/u
ser_guide/indexing.html#returning-a-view-versus-a-copy
  out_of_sample_long_form['model_prediction'] = y_pred
```

Out[62]:

	ticker	cusip	numest	numrec	buypct	sellpct	permno	earnings_reaction_retu
date								
2019-01-04	LW	51327210	6.0	6.0	33.33	0.0	16431	3.562
2019-01-09	CDG2	21036P10	20.0	24.0	66.67	8.33	69796	-12.4173
2019-01-09	LEN	52605710	14.0	19.0	84.21	0.0	52708	7.9272
2019-01-15	UNIH	91324P10	22.0	24.0	95.83	0.0	92655	3.551
2019-01-15	CHL	46625H10	23.0	30.0	53.33	3.33	47896	0.7331
...	...	...	...	...	...	...	...	
2024-12-19	DRAM	59511210	24.0	39.0	87.18	2.56	53613	-16.1790
2024-12-19	KMX	14313010	12.0	18.0	50.0	16.67	89508	3.451
2024-12-20	NIKE	65410610	25.0	41.0	48.78	4.88	57665	-0.2075
2024-12-20	FDX	31428X10	23.0	33.0	69.7	6.06	60628	-0.0543
2024-12-20	CCL	14365830	18.0	27.0	77.78	11.11	75154	6.4336

11725 rows × 25 columns

In [63]:

```
longs = out_of_sample_long_form[out_of_sample_long_form['model_prediction'] == 2]
longs
```

Out[63]:

date	ticker	cusip	numest	numrec	buypct	sellpct	permno	earnings_reaction_retu
2019-01-09	CDG2	21036P10	20.0	24.0	66.67	8.33	69796	-12.4173
2019-01-15	UNIH	91324P10	22.0	24.0	95.83	0.0	92655	3.551
2019-01-15	DAL	24736170	19.0	20.0	95.0	0.0	91926	0.1675
2019-01-16	BLKI	09247X10	13.0	15.0	86.67	0.0	87267	3.0770
2019-01-17	PPG	69350610	22.0	24.0	41.67	0.0	22509	4.7006
...	...	...	...	...	...	...	...	
2024-12-19	CTAS	17290810	15.0	19.0	42.11	10.53	23660	-10.5680
2024-12-19	LW	51327210	8.0	12.0	50.0	0.0	16431	-20.0971
2024-12-19	LEN	52605710	15.0	21.0	42.86	4.76	52708	-5.1600
2024-12-19	DRAM	59511210	24.0	39.0	87.18	2.56	53613	-16.1790
2024-12-19	KMX	14313010	12.0	18.0	50.0	16.67	89508	3.451

4688 rows × 25 columns

In [64]:

```
shorts =  out_of_sample_long_form[out_of_sample_long_form['model_prediction'] == 0]
shorts
```

Out[64]:

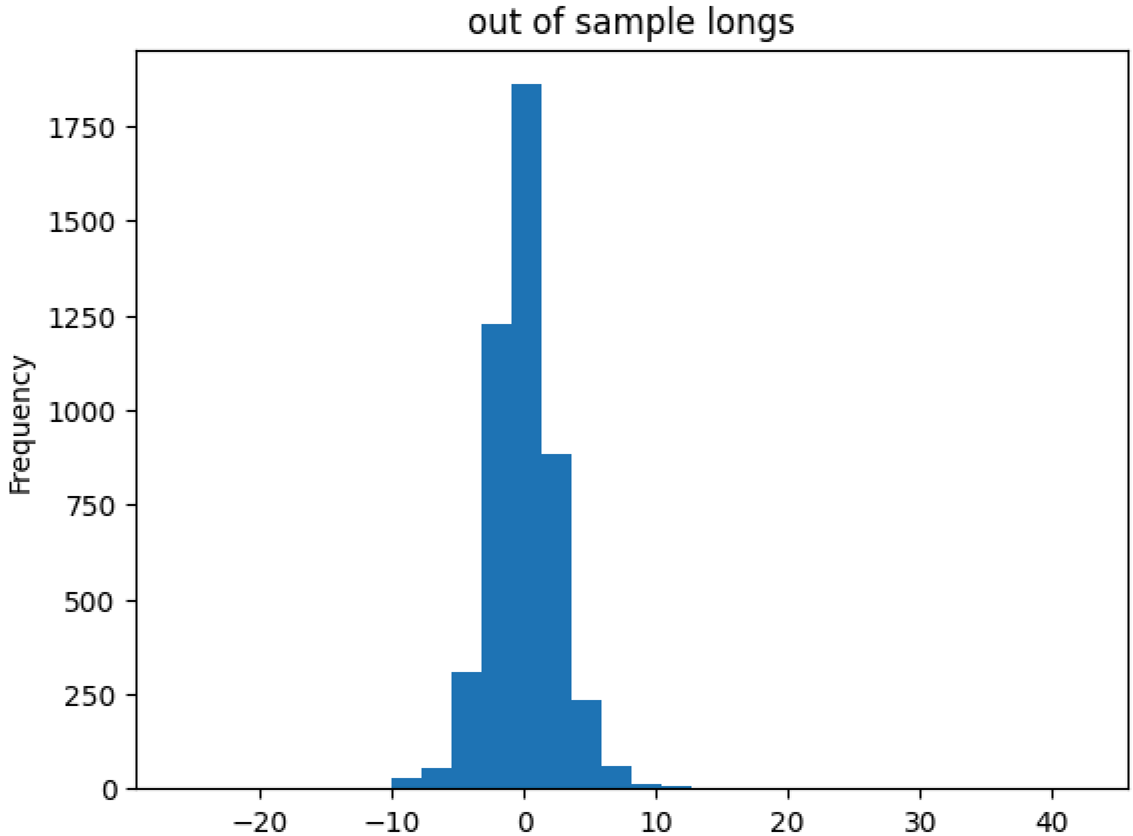
date	ticker	cusip	numest	numrec	buypct	sellpct	permno	earnings_reaction_retu
2019-01-04	LW	51327210	6.0	6.0	33.33	0.0	16431	3.562
2019-01-09	LEN	52605710	14.0	19.0	84.21	0.0	52708	7.9272
2019-01-15	CHL	46625H10	23.0	30.0	53.33	3.33	47896	0.7331
2019-01-15	MRKT	G4756710	17.0	18.0	66.67	5.56	14704	2.2557
2019-01-15	FRCA	33616C10	23.0	23.0	34.78	0.0	12448	11.8449
...	...	...	...	...	...	...	...	
2024-12-13	AOVG	11135F10	28.0	40.0	90.0	0.0	93002	24.4326
2024-12-19	DRI	23719410	26.0	31.0	64.52	3.23	81655	14.7432
2024-12-19	FD1	30307510	17.0	21.0	14.29	28.57	83597	3.5260
2024-12-20	FDX	31428X10	23.0	33.0	69.7	6.06	60628	-0.0543
2024-12-20	CCL	14365830	18.0	27.0	77.78	11.11	75154	6.4336

2725 rows × 25 columns

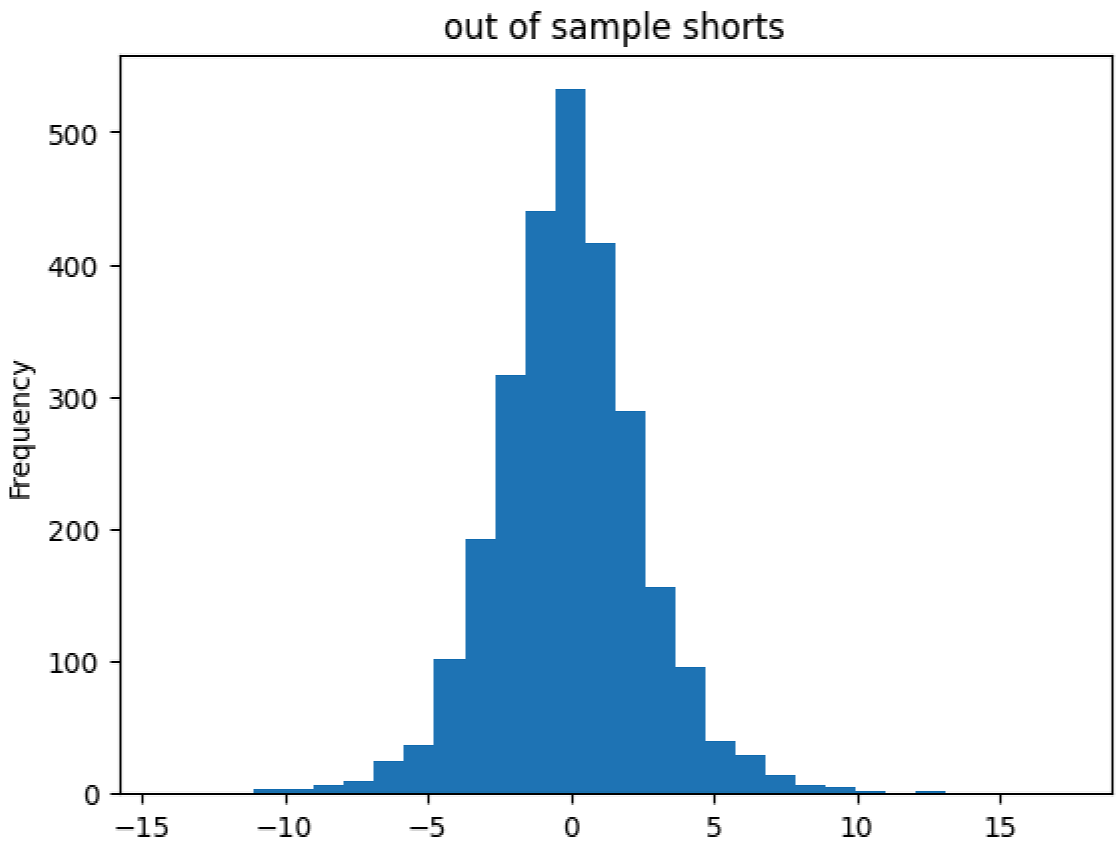
Here is the distribution of returns for out of sample

In [65]:

```
longs['(0, 1 close)_return'].plot(kind = 'hist', bins = 30, title = "out of sample
plt.show()
display(longs['(0, 1 close)_return'].describe())
shorts['(0, 1 close)_return'].plot(kind = 'hist', bins = 30, title = "out of sample
display(plt.show())
shorts['(0, 1 close)_return'].describe()
```




```
count        4688.0
mean       0.002077
std        2.793229
min      -25.913838
25%       -1.475565
50%       -0.078558
75%         1.45605
max       42.355009
Name: (0, 1 close)_return, dtype: Float64
```



None

Out[65]:

```
count        2725.0
mean       -0.09035
std        2.644642
min      -14.214835
25%       -1.656663
50%       -0.123656
75%        1.431889
max       17.295389
Name: (0, 1 close)_return, dtype: Float64
```

The average return is in the direction of our position on both sets, but it is pretty much just zero for both, which is why this is not worth backtesting, particularly due to the small return relative to volatility, the sharpe ratio on this strategy would be horrible.

To summarize:

This classification model is not a usable for a long short strategy, and a future addition to this project would be to implement it with XGBoost and build out a custom loss function to overpenalize putting longs in shorts and shorts in longs.