In [1]:
```
import pandas as pd
```

0.) Clean the Apple Data to get a quarterly series of EPS.

In [2]:
```
y =pd.read_csv("AAPL_quarterly_financials.csv")
```

In [3]:
```
y.index = y.name
```

In [4]:
```
y = pd.DataFrame(y.loc['BasicEPS', :]).iloc[2:, :]
```

In [5]:
```
y.index = pd.to_datetime(y.index)
```

In [6]:
```
y = y.sort_index().fillna(0.) #check if these are time where earning where
```

In [ ]:
```
#X_train, X_test, y_train
```

In [7]:
```
y
```

Out[7]:

	BasicEPS
1985-09-30	0.0
1985-12-31	0.004
1986-03-31	0.002
1986-06-30	0.002
1986-09-30	0.0
...	...
2022-09-30	1.29
2022-12-31	1.89
2023-03-31	1.53
2023-06-30	1.27
2023-09-30	1.47

153 rows × 1 columns

In [8]:
```
y = y.loc["2004-03-31":]
```

In [9]:
```
y
```

Out[9]:

	BasicEPS
2004-03-31	0.002
2004-06-30	0.003
2004-09-30	0.0
2004-12-31	0.013
2005-03-31	0.013
...	...
2022-09-30	1.29
2022-12-31	1.89
2023-03-31	1.53
2023-06-30	1.27
2023-09-30	1.47

79 rows × 1 columns

1.) Come up with 6 search terms you think could nowcast earnings. (Different than the ones I used) Add in 3 terms that that you think will not Nowcast earnings. Pull in the gtrends data. Clean it to have a quarterly average.

In [10]:
```
from pytrends.request import TrendReq
```

In [ ]:
```
# # Create pytrends object
# pytrends = TrendReq(hl='en-US', tz=360)

# # Set up the keywords and the timeframe
# keywords = ["iPhone", "Samsung", "Interest Rates", "New Phone", "Phone r
# start_date = '2004-01-01'
# end_date = '2024-01-01'

# # Create an empty DataFrame to store the results
# df = pd.DataFrame()

# # Iterate through keywords and fetch data
# for keyword in keywords:
#     pytrends.build_payload([keyword], cat=0, timeframe=f'{start_date} {e
#     interest_over_time_df = pytrends.interest_over_time()
#     df[keyword] = interest_over_time_df[keyword]
```

In [13]:
```
# Create pytrends object
pytrends = TrendReq(hl='en-US', tz=360)

# Set up the keywords and the timeframe
keywords = ["Mac", "June", "Camera", "iPad", "CEO", "Innovation", "Dodger
start_date = '2004-01-01'
end_date = '2023-09-30'
#end_date = '2024-01-01'

# Create an empty DataFrame to store the results
df = pd.DataFrame()

# Iterate through keywords and fetch data
for keyword in keywords:
    pytrends.build_payload([keyword], cat=0, timeframe=f'{start_date} {enc
    interest_over_time_df = pytrends.interest_over_time()
    df[keyword] = interest_over_time_df[keyword]
```

In [ ]:
```
df
```

In [14]:
```
df = df.resample("Q").mean()
```

In [ ]:
```
# # Create pytrends object
# pytrends = TrendReq(hl='en-US', tz=360)

# # Set up the keywords and the timeframe
# keywords = ['Example Phrase 1", "Example Phrase 2"]  # Add your keywords
# start_date = '2004-01-01'
# end_date = '2024-01-01'

# # Create an empty DataFrame to store the results
# df = pd.DataFrame()

# # Iterate through keywords and fetch data
# for keyword in keywords:
#     pytrends.build_payload([keyword], cat=0, timeframe=f'{start_date} {e
#     interest_over_time_df = pytrends.interest_over_time()
#     df[keyword] = interest_over_time_df[keyword]
```

2.) Normalize all the X data

In [15]:
```
from sklearn.preprocessing import StandardScaler
from sklearn.model_selection import train_test_split
```

In [16]:
```
scaler = StandardScaler()
X_scaled = scaler.fit_transform(df)
```

In [ ]:
```
X_scaled
```

3.) Import data. Train, Test, Holdout (80%,15%,5%)

In [17]:
```
X_train, X_temp, y_train, y_temp = train_test_split(X_scaled, y, test_size
```

In [18]:
```
X_test, X_holdout, y_test, y_holdout = train_test_split(X_temp, y_temp, te
```

In [ ]:
```
X_train
```

4.) Run a Lasso with lambda of .5. Plot a bar chart.

In [19]:
```
from sklearn.linear_model import Lasso
```

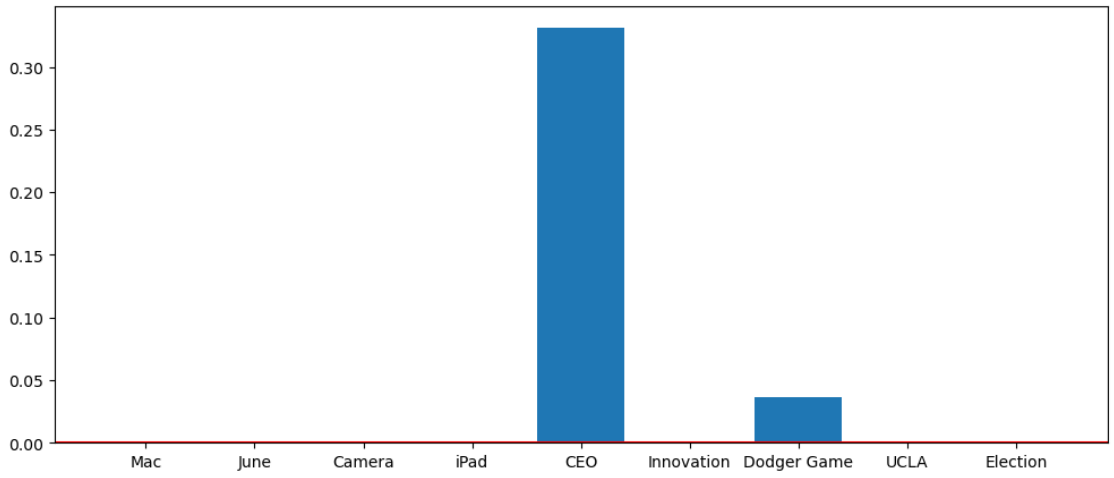
In [55]:
```
lasso = Lasso(alpha = .1) #.5
lasso.fit(X_scaled, y)

coefficients = lasso.coef_ #check which
```

In [33]:
```
coefficients
```

Out[33]:
```
array([-0.,  0., -0.,  0.,  0., -0.,  0., -0.,  0.])
```

In [29]:
```
import matplotlib.pyplot as plt
```

In [58]:
```
plt.figure(figsize = (12,5))
#plt.bar(range(len(coefficients)), coefficients, df.columns)
plt.bar(df.columns, coefficients)
plt.axhline(0, color = "red")
#insert label....
plt.show()
```



In [ ]:
```
```

In [47]:
```
df.columns
```

Out[47]:
```
Index(['Mac', 'June', 'Camera', 'iPad', 'CEO', 'Innovation', 'Dodger Gam
e',
       'UCLA', 'Election'],
      dtype='object')
```

In [48]:
```
df
```

Out[48]:

date	Mac	June	Camera	iPad	CEO	Innovation	Dodger Game	U
2004-03-31	70.666667	6.666667	87.666667	0.000000	38.000000	91.333333	0.333333	88.33
2004-06-30	66.333333	25.666667	85.333333	0.000000	36.666667	86.666667	0.666667	82.66
2004-09-30	65.333333	6.666667	81.666667	0.000000	37.000000	80.000000	0.333333	74.33
2004-12-31	71.666667	4.666667	92.000000	0.000000	37.666667	83.333333	0.333333	85.00
2005-03-31	77.333333	6.333333	74.000000	0.000000	47.666667	86.666667	0.000000	82.66
...	...	...	...	...	...	...	...	
2022-09-30	40.000000	12.000000	54.666667	23.666667	93.000000	78.000000	13.000000	33.00
2022-12-31	40.666667	8.000000	53.666667	27.000000	87.333333	79.000000	4.666667	40.66
2023-03-31	40.000000	10.666667	56.000000	23.666667	91.000000	85.000000	1.000000	41.33
2023-06-30	36.000000	43.666667	54.000000	21.333333	90.333333	74.666667	8.666667	29.00
2023-09-30	35.666667	11.000000	54.666667	23.000000	94.000000	80.333333	8.000000	29.00

79 rows × 9 columns

In [ ]:
```
```

5.) Do these coefficient magnitudes make sense?

Yes, these coefficients are sensible values. CEO is quite related to the other coefficients listed and subsequently might capture the information contained in the data. It is also the most common term and that might also be a reason for its strong value. Interesting the Dodger have a very small coefficient value, indicating there might be some relationship that ought to be investigate or it might be capturing another correlated value.

In [ ]:
```
###Stop at 5!!!!!
```

6.) Run a for loop looking at 10 different Lambdas and plot the coefficient magnitude for each.

In [ ]:

In [ ]:

7.) Run a cross validation. What is your ideal lambda?

In [ ]:

In [ ]: