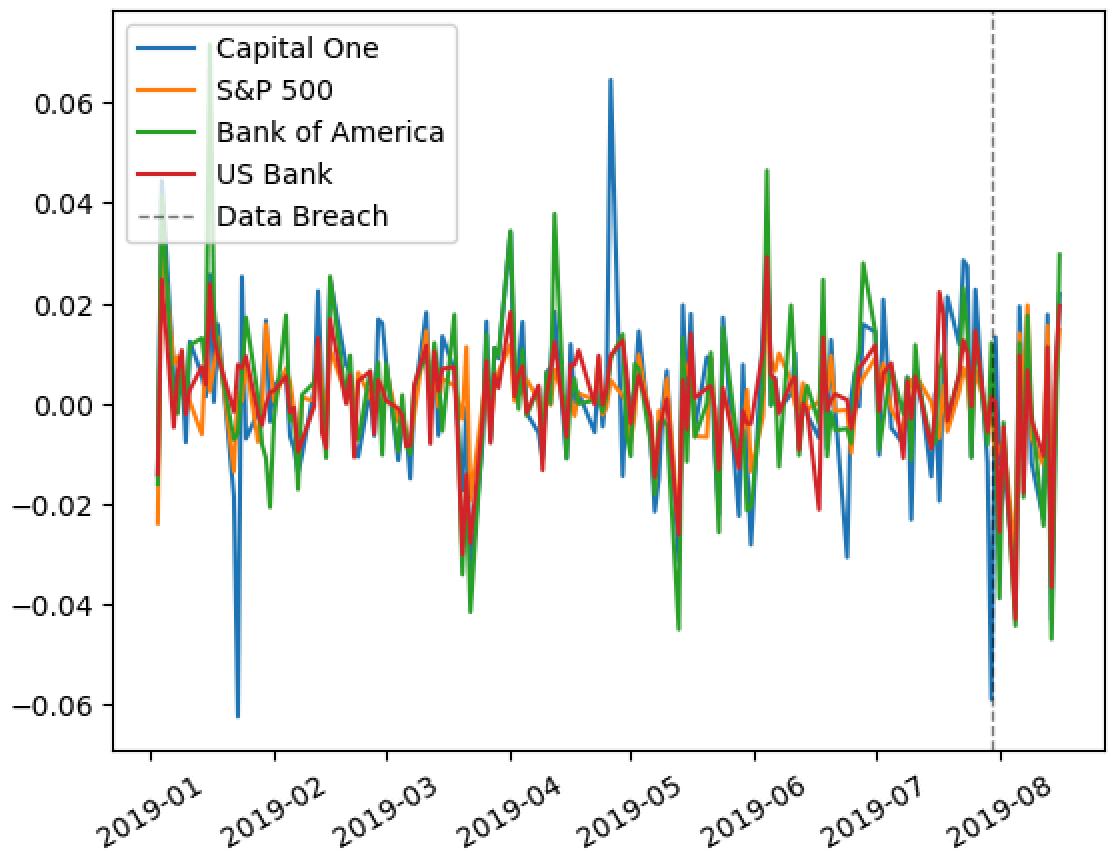
Capital One 2019 Data breach announced on July 29th

In [1]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import datetime
import statsmodels.formula.api as smf
from yahoo_fin import stock_info as si
import yfinance as yf
```

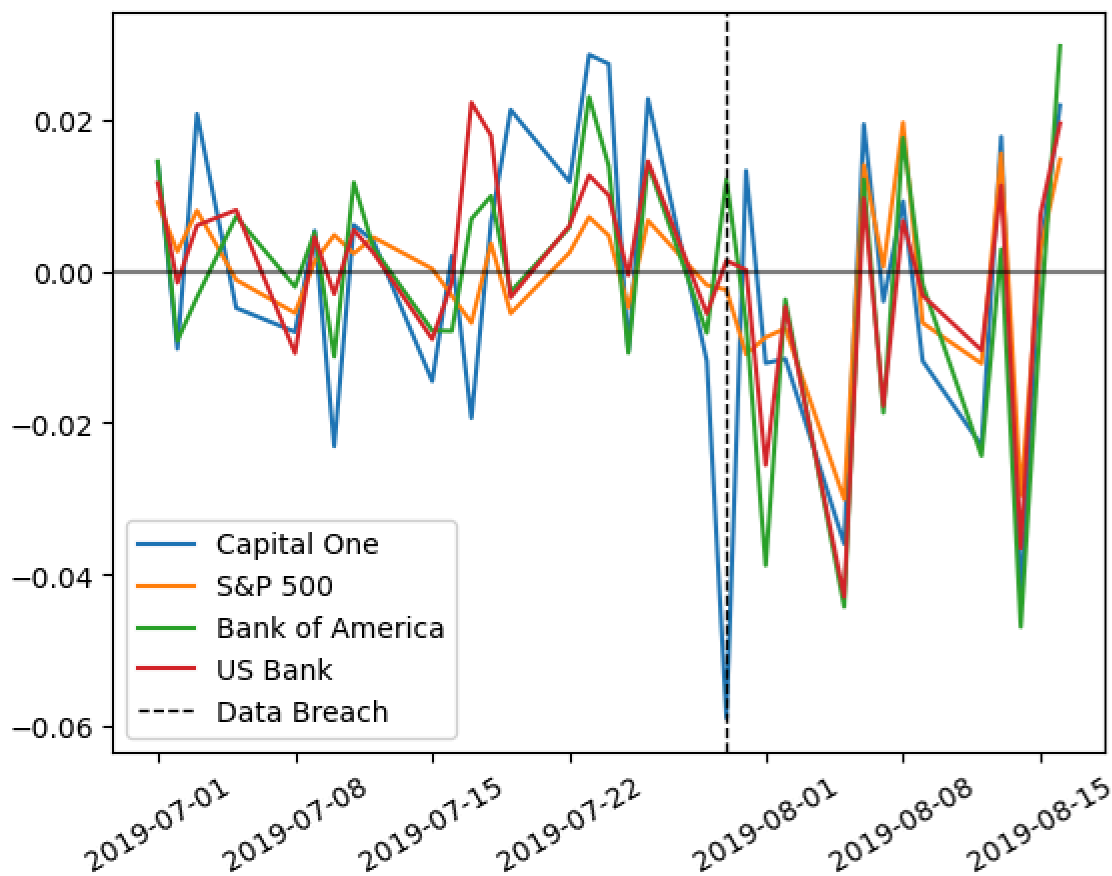
In [2]:
```
def get_daily_prices(ticker, start_date, end_date):
    df = si.get_data(ticker, interval='1d', start_date=start_date, end_date=e
    df['price'] = df['adjclose']
    df['date'] = df.index
    df['ticker'] = ticker
    df = df[['date', 'price', 'ticker']]
    return df

def get_prices(tickerlist, start, end):
    df = pd.DataFrame(columns=['date', 'price', 'ticker'])
    for ticker in tickerlist:
        df = pd.concat([df, get_daily_prices(ticker, start, end)], ignore_ind
    return df

def run_diff_in_diff(df, event_date, treated):
    start_date = event_date - datetime.timedelta(days=180)
    df = df[(df['date'] >= start_date) & (df['date'] <= event_date)].copy()

    df['returns'] = df.groupby('ticker')['price'].pct_change()
    df = df.dropna(subset=['returns'])  # Drop rows where 'returns' is NaN

    df.loc[:, 'treated'] = np.where(df['ticker'] == treated, 1, 0)
    df.loc[:, 'post'] = np.where(df['date'] >= event_date, 1, 0)
    df.loc[:, 'treated_post'] = df['treated'] * df['post']

    formula = "returns ~ treated + post + treated_post"
    model = smf.ols(formula=formula, data=df).fit()
    return model

def difference_in_trends(df, event_date, treated):
    start_date = event_date - datetime.timedelta(days=180)
    df = df[(df['date'] >= start_date) & (df['date'] <= event_date)].copy()

    # Create the 'returns' column
    df['returns'] = df.groupby('ticker')['price'].pct_change()
    df = df.dropna(subset=['returns'])  # Drop rows where 'returns' is NaN

    df.loc[:, 'treated'] = np.where(df['ticker'] == treated, 1, 0)
    df.loc[:, 'trend'] = (event_date - df['date']).dt.days
    df.loc[:, 'treated_trend'] = df['treated'] * df['trend']

    formula = "returns ~ treated + trend + treated_trend"
    model = smf.ols(formula=formula, data=df).fit()
    return model
```

In [3]:
```
start_date = '01-01-2019'
end_date = '08-19-2019'
event_date = pd.to_datetime('07-30-2019')

tickerlist = list(['COF', 'SPY', 'VTI', 'BAC', 'USB', 'C', 'JPM', 'WFC'])
prices = get_prices(tickerlist, start_date, end_date)
prices['return'] = np.where(prices['ticker'] == prices['ticker'].shift(),
                            prices['price'] / prices['price'].shift() - 1,
                            np.nan)

prices.dropna(subset=['return'], inplace=True)
prices['date'] = pd.to_datetime(prices['date'])
```

In [4]:
```
prices['returns'] = np.where(prices['ticker'] == prices['ticker'].shift(),
                             prices['price'] / prices['price'].shift() - 1,
                             np.nan)
eventDate = pd.to_datetime('07-30-2019')

cof=prices[prices['ticker']=='COF']
spy=prices[prices['ticker']=='SPY']
bac=prices[prices['ticker']=='BAC']
usb=prices[prices['ticker']=='USB']

plt.plot(cof['date'], cof['return'], label='Capital One')
plt.plot(spy['date'], spy['return'], label='S&P 500')
plt.plot(bac['date'], bac['return'], label='Bank of America')
plt.plot(usb['date'], usb['return'], label='US Bank')
plt.axvline(eventDate, color='black', linestyle='--', linewidth=1, alpha=.5, 
plt.xticks(rotation=30)
plt.legend(loc="upper left")
plt.show()
```



In [5]:
```
prices['returns'] = np.where(prices['ticker'] == prices['ticker'].shift(),
                             prices['price'] / prices['price'].shift() - 1,
                             np.nan)
eventDate = pd.to_datetime('07-30-2019')

prices['date'] = pd.to_datetime(prices['date'])
focused_prices = prices[(prices['date'] >= pd.to_datetime('07-01-2019')) & (pr

cof=focused_prices[focused_prices['ticker']=='COF']
spy=focused_prices[focused_prices['ticker']=='SPY']
bac=focused_prices[focused_prices['ticker']=='BAC']
usb=focused_prices[focused_prices['ticker']=='USB']

plt.plot(cof['date'], cof['return'], label='Capital One')
plt.plot(spy['date'], spy['return'], label='S&P 500')
plt.plot(bac['date'], bac['return'], label='Bank of America')
plt.plot(usb['date'], usb['return'], label='US Bank')
plt.axhline(y=0, color='black', alpha=.5)
plt.axvline(eventDate, color='black', linestyle='--', linewidth=1, label = 'Da
plt.xticks(rotation=30)
plt.legend(loc="lower left")
plt.show()
```



In [6]:
```
prices[prices['date']>='07-25-2019'].iloc[:10]
```

Out[6]:

	date	price	ticker	return	returns
141	2019-07-25	87.911079	COF	-0.010524	-0.010524
142	2019-07-26	89.909462	COF	0.022732	0.022732
143	2019-07-29	88.846100	COF	-0.011827	-0.011827
144	2019-07-30	83.611786	COF	-0.058914	-0.058914
145	2019-07-31	84.720993	COF	0.013266	0.013266
146	2019-08-01	83.694283	COF	-0.012119	-0.012119
147	2019-08-02	82.727524	COF	-0.011551	-0.011551
148	2019-08-05	79.753555	COF	-0.035949	-0.035949
149	2019-08-06	81.300400	COF	0.019395	0.019395
150	2019-08-07	80.978127	COF	-0.003964	-0.003964

Estimate Difference-in-Differences Model

In [7]:
```
treated = 'COF'
model = run_diff_in_diff(prices, event_date, treated)
print(model.summary())
```

```
                            OLS Regression Results
==============================================================================
==
Dep. Variable:                returns   R-squared:                       0.0
28
Model:                            OLS   Adj. R-squared:                  0.0
25
Method:                 Least Squares   F-statistic:                     9.4
28
Date:                Sat, 15 Jun 2024   Prob (F-statistic):           3.81e-
06
Time:                        12:04:17   Log-Likelihood:                 303
4.8
No. Observations:                 992   AIC:                            -606
2.
Df Residuals:                     988   BIC:                            -604
2.
Df Model:                           3
Covariance Type:            nonrobust
==============================================================================
====
                   coef    std err          t      P>|t|      [0.025      0.
975]
------------------------------------------------------------------------------
----
Intercept        0.0009      0.000      2.202      0.028    9.28e-05
0.002
treated          0.0008      0.001      0.756      0.450      -0.001
0.003
post             0.0010      0.004      0.224      0.823      -0.008
0.009
treated_post    -0.0616      0.012     -5.041      0.000      -0.086      -
0.038
==============================================================================
==
Omnibus:                       79.277   Durbin-Watson:                   1.9
97
Prob(Omnibus):                  0.000   Jarque-Bera (JB):              406.2
24
Skew:                           0.083   Prob(JB):                     6.16e-
89
Kurtosis:                       6.131   Cond. No.                          3
4.4
==============================================================================
==

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is corre
ctly specified.
```

The -0.0616 treated post indicates the event is resposible for about a 6% drop in market price

Test Validation Assumptions

Assumption 1: There is no difference in trend prior to the event

In [8]:
```
placebo_date = event_date - datetime.timedelta(days=1)
treated='COF'

test_trend_model = difference_in_trends(prices, placebo_date, treated)
print(test_trend_model.summary())
```

```
                            OLS Regression Results                            
==============================================================================
==
Dep. Variable:                returns   R-squared:                       0.0
02
Model:                            OLS   Adj. R-squared:                 -0.0
01
Method:                 Least Squares   F-statistic:                    0.73
67
Date:                Sat, 15 Jun 2024   Prob (F-statistic):              0.5
30
Time:                        12:04:18   Log-Likelihood:                 303
2.5
No. Observations:                 992   AIC:                            -605
7.
Df Residuals:                     988   BIC:                            -603
7.
Df Model:                           3                                         
Covariance Type:            nonrobust                                         
==============================================================================
=====
                    coef    std err          t      P>|t|      [0.025      
0.975]
------------------------------------------------------------------------------
-----
Intercept         0.0016      0.001      2.128      0.034       0.000       
0.003
treated           0.0007      0.002      0.302      0.763      -0.004       
0.005
trend         -9.187e-06   7.47e-06     -1.229      0.219   -2.39e-05    5.4
8e-06
treated_trend  1.732e-06   2.11e-05      0.082      0.935   -3.98e-05    4.3
2e-05
==============================================================================
==
Omnibus:                       77.697   Durbin-Watson:                   1.9
95
Prob(Omnibus):                  0.000   Jarque-Bera (JB):              391.3
97
Skew:                           0.074   Prob(JB):                     1.02e-
85
Kurtosis:                       6.074   Cond. No.                         63
8.
==============================================================================
==

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is corre
ctly specified.
```

Here the treated trend value is extremely close to 0 and even has a p-value of 0.85 so it is not even close to statistically significant. ie. In the pre period there is no real difference in trend and so no reason to believe that it would change afterwards

Assumption 2: The model is not biased (estimates close to zero when no effect)

In [9]:
```
placebo_date = event_date - datetime.timedelta(days=1)
treated='COF'

placebo_model = run_diff_in_diff(prices, placebo_date, treated)
print(placebo_model.summary())
```

```
                            OLS Regression Results
==============================================================================
==
Dep. Variable:                returns   R-squared:                       0.0
05
Model:                            OLS   Adj. R-squared:                  0.0
02
Method:                 Least Squares   F-statistic:                     1.7
00
Date:                Sat, 15 Jun 2024   Prob (F-statistic):              0.1
65
Time:                        12:04:18   Log-Likelihood:                 303
4.0
No. Observations:                 992   AIC:                            -606
0.
Df Residuals:                     988   BIC:                            -604
0.
Df Model:                           3
Covariance Type:            nonrobust
==============================================================================
====
                   coef    std err          t      P>|t|      [0.025      0.
975]
------------------------------------------------------------------------------
----
Intercept        0.0009      0.000      2.281      0.023       0.000
0.002
treated          0.0009      0.001      0.788      0.431      -0.001
0.003
post            -0.0076      0.004     -1.770      0.077      -0.016
0.001
treated_post    -0.0059      0.012     -0.485      0.628      -0.030
0.018
==============================================================================
==
Omnibus:                       78.529   Durbin-Watson:                   1.9
81
Prob(Omnibus):                  0.000   Jarque-Bera (JB):              401.2
18
Skew:                           0.070   Prob(JB):                      7.53e-
88
Kurtosis:                       6.112   Cond. No.                          3
4.4
==============================================================================
==

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is corre
ctly specified.
```

Again we get a treated post near 0 and a p value still no where near .05 and so not stastically significant

In [10]:
```
placebo_start = event_date - datetime.timedelta(days=120)
pre_event_dates = prices[(prices['date'] >= placebo_start) & (prices['date'] 
pvalues = list()
betas = list()

for placebo_date in pre_event_dates:
    placebo_model=run_diff_in_diff(prices, pd.to_datetime(placebo_date), trea
    pvalues.append(placebo_model.pvalues['treated_post'])
    betas.append(placebo_model.params['treated_post'])
```

In [11]:
```
df = pd.DataFrame({'betas':betas, 'pvalues':pvalues})
print(display(df.describe()))
```

	betas	pvalues
count	664.000000	664.000000
mean	0.000692	0.646151
std	0.010636	0.261996
min	-0.025293	0.000011
25%	-0.004635	0.486030
50%	0.000642	0.720415
75%	0.005038	0.860783
max	0.056549	0.998293

None

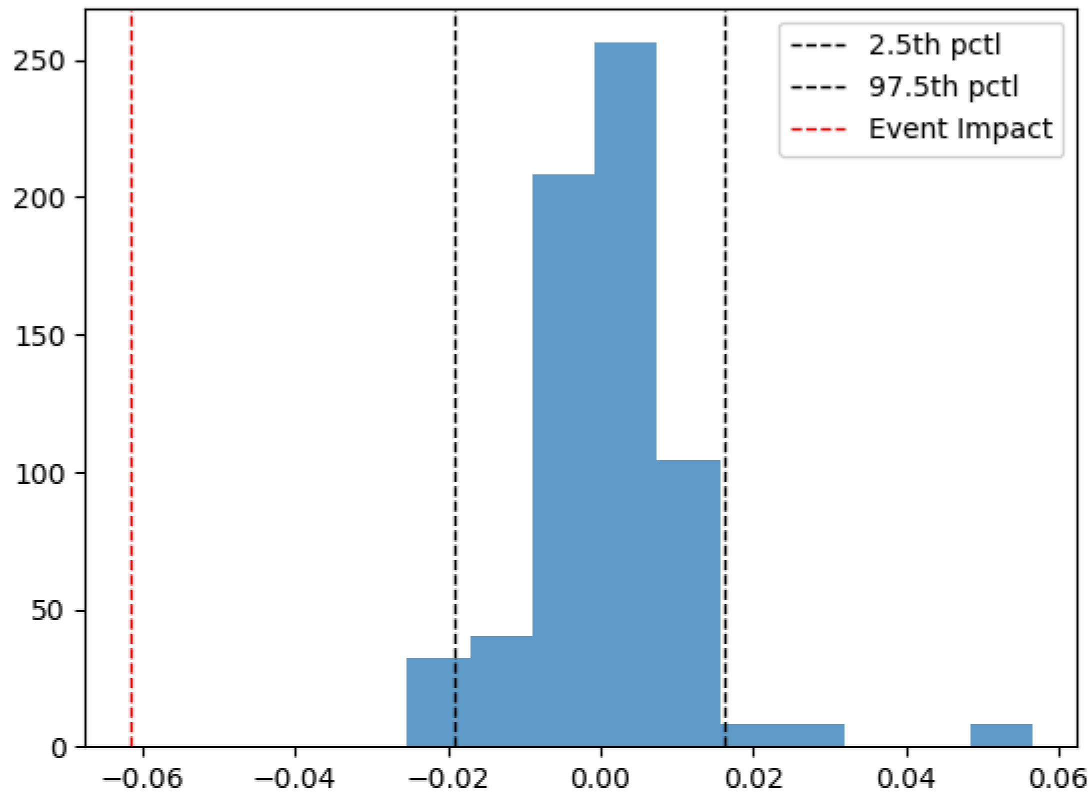
In [12]:
```
#Not Working
print("Share of pvalue < 0.5: {:.2f}%".format(100 * len(df[df['pvalues'] < 0.
```

```
Share of pvalue < 0.5: 27.71%
```

In [13]:
```
df['betas'].quantile([0.025,0.975])
```

Out[13]:
```
0.025   -0.019087
0.975    0.016195
Name: betas, dtype: float64
```

In [14]:
```
quantile_2_5 = df['betas'].quantile(0.035)
quantile_97_5 = df['betas'].quantile(0.975)
model_est = model.params['treated_post']

plt.hist(df['betas'], bins=10, alpha=0.7)
plt.axvline(quantile_2_5, color='black', linestyle='--', linewidth=1, label =
plt.axvline(quantile_97_5, color='black', linestyle='--', linewidth=1, label =
plt.axvline(model_est, color='red', linestyle='--', linewidth=1, label = 'Ever
plt.legend(loc='upper right')
plt.show()
```



In [15]:

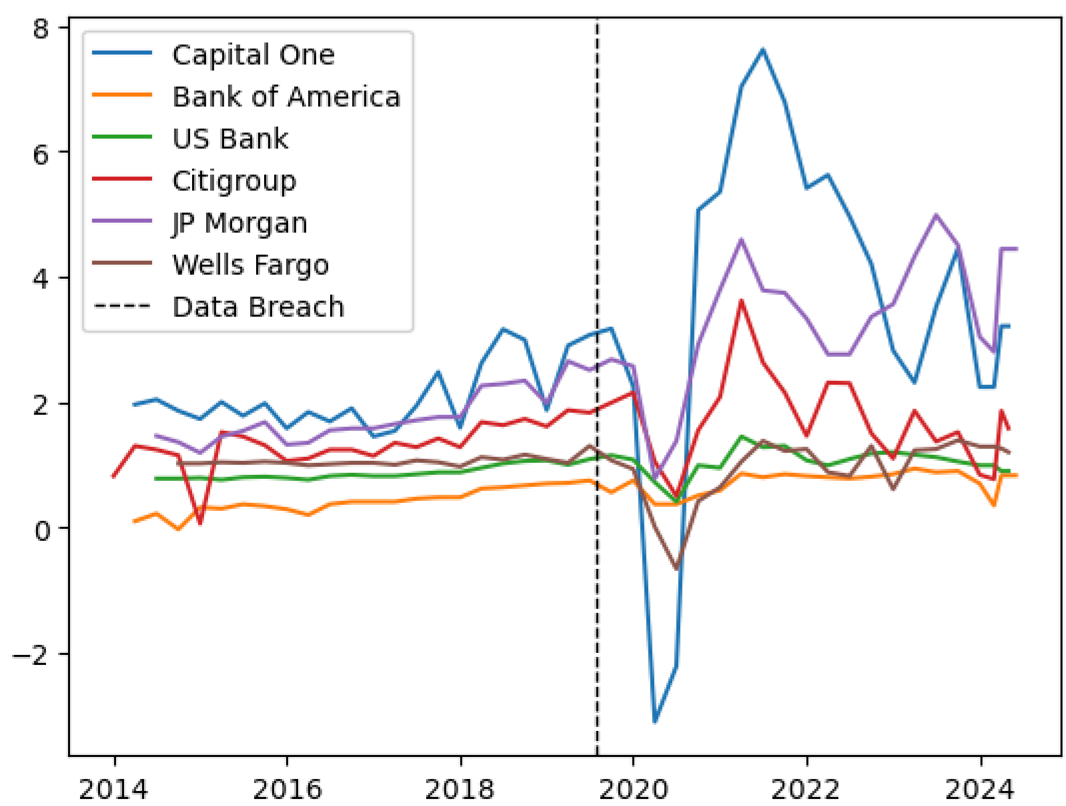
```
tickers = yf.Tickers("COF BAC USB C JPM WFC")

cofEarnings = tickers.tickers['COF'].get_earnings_dates(limit=50)
bacEarnings = tickers.tickers['BAC'].get_earnings_dates(limit=150)
usbEarnings = tickers.tickers['USB'].get_earnings_dates(limit=60)
cEarnings = tickers.tickers['C'].get_earnings_dates(limit=85)
jpmEarnings = tickers.tickers['JPM'].get_earnings_dates(limit=137)
wfcEarnings = tickers.tickers['WFC'].get_earnings_dates(limit=75)

earningsList = [cofEarnings, bacEarnings, usbEarnings, cEarnings, jpmEarnings,

for company in earningsList:
    company.dropna(inplace=True)
    company.index = company.index.date
    company.drop_duplicates(inplace=True)
    company['Date'] = company.index
    company.reset_index(inplace=True)
    company.drop(columns=["index"], inplace=True)
    company['Date']=pd.to_datetime(company['Date'])
    company['Month'] = company['Date'].dt.to_period('M')
    company.drop('Date', axis=1, inplace=True)
    company['Month'] = company['Month'].dt.to_timestamp()


common_months = set(wfcEarnings['Month'])
for earnings in earningsList[1:]:
    common_months &= set(earnings['Month'])

filtered_earnings = []
for earnings in earningsList:
    filtered_earnings.append(earnings[earnings['Month'].isin(common_months)])

cofEarnings, bacEarnings, usbEarnings, cEarnings, jpmEarnings, wfcEarnings = 

jpmEarnings
```

Out[15]:

	EPS Estimate	Reported EPS	Surprise(%)	Month
1	4.11	4.44	0.0792	2024-04-01
2	3.06	2.80	-0.0850	2024-03-01
3	3.32	3.04	-0.0850	2024-01-01
4	3.96	4.50	0.1371	2023-10-01
5	4.00	4.98	0.2465	2023-07-01
6	3.41	4.32	0.2664	2023-04-01
7	3.07	3.56	0.1614	2023-01-01
8	2.88	3.36	0.1656	2022-10-01
9	2.88	2.76	-0.0425	2022-07-01
10	2.69	2.76	0.0267	2022-04-01
11	3.01	3.33	0.1057	2022-01-01

In [16]:

```
companies = ['Capital One', 'Bank of America', 'US Bank', 'Citigroup', 'JP Mor
eventDate = pd.to_datetime('07-30-2019')



for index, company in enumerate(earningsList):
    plt.plot(company['Month'], company['Reported EPS'], label = companies[inde
plt.axvline(eventDate, color='black', linestyle='--', linewidth=1, label = 'Da
plt.legend()
plt.show()
```



In [ ]: