Here is the code for our MGMT-172 project. We used various stock analysis techiques to find data regarding Kroger acquisitions. In the code block below is all the imports neccessary to generate the plots we used. If you are having trouble you might not have downloaded a requirement in pip. Additionally, the time objects are created in the block below.

In [57]:
```
#Imports
#!pip install yfinance
#!pip install fix_yahoo_finance
#!pip install plotly-express
import pandas as pd
import seaborn as sns
import numpy as np
import pylab as py
import matplotlib.pyplot as plt
import yfinance as yf
#from yahoofinancials import YahooFinancials
pd.core.common.is_list_like = pd.api.types.is_list_like
from pandas_datareader import data, wb
import plotly.express as px

import datetime
from datetime import date
%matplotlib inline

start = datetime.datetime(2020, 1, 1)

end = date.today()
```

This is a dataset generated from Yahoo Finance using the time frame.

In [2]:
```
#Data set 1
df2 = data.DataReader(['WMT', 'TGT', 'COST', 'KR', 'ACI'],'yahoo', start, end)
df2.head(10)
#Add wholefoods and amazon
```

Out[2]:

| **Attributes** | | | **Adj Close** | | | | | | **Close** | ... | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **Symbols** | **WMT** | **TGT** | **COST** | **KR** | **ACI** | **WMT** | **TGT** | **COST** | **KR** | **ACI** | ... | **WMT** | **TGT** | **COST** |
| **Date** | | | | | | | | | | | | | | |
| **2020-01-02** | 113.801064 | 119.371849 | 277.666962 | 26.969685 | NaN | 118.940002 | 126.070000 | 291.489990 | 28.660000 | NaN | ... | 118.860001 | 128.740005 | 294.059998 |
| **2020-01-03** | 112.796432 | 118.131432 | 277.895599 | 27.007322 | NaN | 117.889999 | 124.760002 | 291.730011 | 28.700001 | NaN | ... | 118.269997 | 124.660004 | 290.049988 |
| **2020-01-06** | 112.566818 | 117.014145 | 277.971832 | 27.101427 | NaN | 117.650002 | 123.580002 | 291.809998 | 28.799999 | NaN | ... | 117.400002 | 123.970001 | 290.549988 |
| **2020-01-07** | 111.523895 | 117.222443 | 277.533661 | 26.903812 | NaN | 116.559998 | 123.800003 | 291.350006 | 28.590000 | NaN | ... | 117.260002 | 123.000000 | 291.320007 |
| **2020-01-08** | 111.141190 | 116.843712 | 280.715240 | 26.743837 | NaN | 116.160004 | 123.400002 | 294.690002 | 28.420000 | NaN | ... | 116.300003 | 124.050003 | 290.989990 |
| **2020-01-09** | 112.289337 | 116.938377 | 285.220947 | 26.762657 | NaN | 117.360001 | 123.500000 | 299.420013 | 28.440001 | NaN | ... | 116.150002 | 123.500000 | 298.549988 |
| **2020-01-10** | 111.351669 | 118.103027 | 283.144257 | 26.687380 | NaN | 116.379997 | 124.730003 | 297.239990 | 28.360001 | NaN | ... | 117.239998 | 124.709999 | 300.000000 |
| **2020-01-13** | 110.873276 | 117.288742 | 285.649567 | 26.743837 | NaN | 115.879997 | 123.870003 | 299.869995 | 28.420000 | NaN | ... | 116.379997 | 124.589996 | 296.920013 |
| **2020-01-14** | 111.160309 | 118.604889 | 285.535309 | 27.139065 | NaN | 116.180000 | 125.260002 | 299.750000 | 28.840000 | NaN | ... | 115.470001 | 123.599998 | 299.250000 |
| **2020-01-15** | 110.299202 | 110.783737 | 286.554504 | 26.621502 | NaN | 115.279999 | 117.000000 | 300.820007 | 28.290001 | NaN | ... | 114.629997 | 117.489998 | 298.350006 |

10 rows × 30 columns

Below are several data frames and a master data frame used to generate specific plots. These are all from Yahoo Finance using the DataReader method.

In [3]:
```
#Data set 2
Walmart = data.DataReader("WMT", 'yahoo', start, end)
Target = data.DataReader("TGT", 'yahoo', start, end)
Costco = data.DataReader("COST", 'yahoo', start, end)
Kroger = data.DataReader("KR", 'yahoo', start, end)
Albertsons = data.DataReader("ACI", 'yahoo', start, end)

Walmart["Company"]='Walmart'
Target["Company"]='Target'
Costco["Company"]='Costco'
Kroger["Company"]='Kroger'
Albertsons["Company"]='Albertsons'

master2 = pd.concat([Walmart,Target,Costco,Kroger,Albertsons],
                   keys=["Walmart","Target","Costco","Kroger","Albertsons"])
master2
#Add wholefoods and amazon
```

Out[3]:

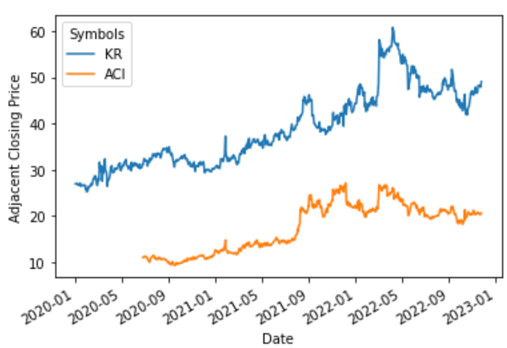
| | | High | Low | Open | Close | Volume | Adj Close | Company |
|---|---|---|---|---|---|---|---|---|
| | **Date** | | | | | | | |
| | **2020-01-02** | 119.889999 | 118.699997 | 118.860001 | 118.940002 | 6764900.0 | 113.801071 | Walmart |
| | **2020-01-03** | 118.790001 | 117.589996 | 118.269997 | 117.889999 | 5399200.0 | 112.796425 | Walmart |
| **Walmart** | **2020-01-06** | 118.089996 | 116.769997 | 117.400002 | 117.650002 | 6445500.0 | 112.566811 | Walmart |
| | **2020-01-07** | 117.519997 | 116.199997 | 117.260002 | 116.559998 | 6846900.0 | 111.523895 | Walmart |
| | **2020-01-08** | 116.730003 | 115.680000 | 116.300003 | 116.160004 | 5875800.0 | 111.141174 | Walmart |
| **...** | **...** | ... | ... | ... | ... | ... | ... | ... |
| | **2022-11-18** | 20.840000 | 20.299999 | 20.730000 | 20.520000 | 6182100.0 | 20.520000 | Albertsons |
| | **2022-11-21** | 20.799999 | 20.430000 | 20.570000 | 20.440001 | 2628500.0 | 20.440001 | Albertsons |
| **Albertsons** | **2022-11-22** | 20.715000 | 20.490000 | 20.490000 | 20.549999 | 2744500.0 | 20.549999 | Albertsons |
| | **2022-11-23** | 20.680000 | 20.420000 | 20.549999 | 20.440001 | 1873400.0 | 20.440001 | Albertsons |
| | **2022-11-25** | 20.690001 | 20.500000 | 20.510000 | 20.670000 | 906100.0 | 20.670000 | Albertsons |

3538 rows × 7 columns

The first plot shows the Adj Closures of Kroger and Albertsons. We thought this would be important to determine if consumers thought the acquisition would be profitable.

In [4]:
```
#Kroger and Albertsons Stock
ak = df2["Adj Close"][["KR","ACI"]]

akfig = ak.plot()

akfig.set_ylabel("Adjacent Closing Price")
```

Out[4]: `Text(0, 0.5, 'Adjacent Closing Price')`




We plotted Amazon during the Whole Foods acquisition to compare the two companies. While they operate in different industries we believe the data can reveal a trend in acquisitions. We needed to create a new date time objects and data frame to accomplish this. This data also came from Yahoo Finance. df3 was created here.

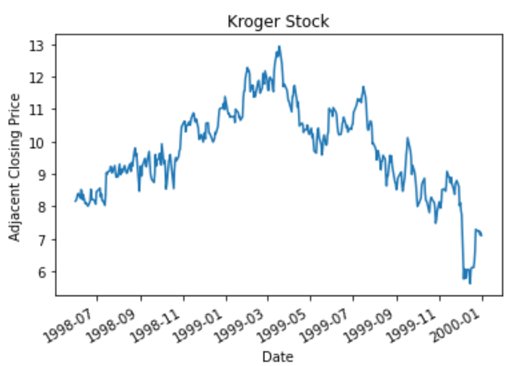
In [5]:
```
#Amazon stock during the time period it bought Whole Foods
s2 = datetime.datetime(2017, 5, 1)

e2 = datetime.datetime(2017, 12, 31)

df3 = data.DataReader('AMZN','yahoo', s2, e2)

aw = df3["Adj Close"]

awfig = aw.plot(title="Amazon Stock")

awfig.set_ylabel("Adjacent Closing Price")
```

Out[5]: Text(0, 0.5, 'Adjacent Closing Price')


In the past Kroger purchased another grocery company. Therefore, we made a plot to show this with new datatime objects and data frame from Yahoo Finance. df4 was created here.

In [64]:
```
# Kroger Bought Ralphs
s3 = datetime.datetime(1998, 6, 1)

e3 = datetime.datetime(1999, 12, 31)

df4 = data.DataReader('KR','yahoo', s3, e3)

tr = df4["Adj Close"]

trfig = tr.plot(title="Kroger Stock")

trfig.set_ylabel("Adjacent Closing Price")
```

Out[64]: Text(0, 0.5, 'Adjacent Closing Price')

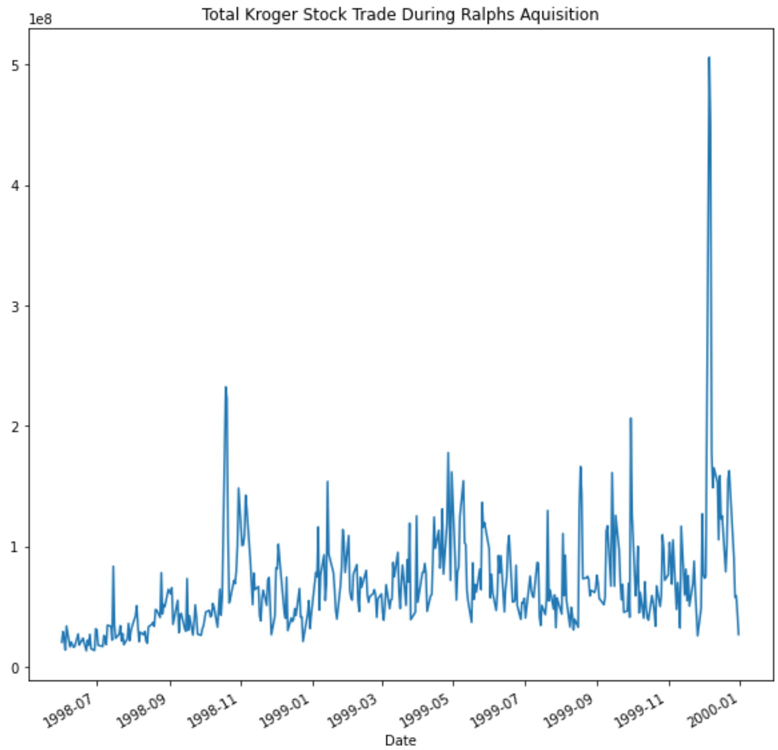



We found that while stock prices increased when acquiring Ralphs they eventually plumeted. Furthermore, Kroger stock dipped after they acquired Albertsons. Intrestingly, Amazon skyrocketed after acquiring Whole Foods. We believe this data reveals the acquisition might not be the best idea.

Using a perviously defined data frame (df4) we multiplied the open and volume of Kroger stock to find the stock trade during the ralphs acquisition.

In [7]:
```
df4["Total Traded"] = df4["Open"]*df4["Volume"]
df4["Total Traded"].plot(title="Total Kroger Stock Trade During Ralphs Aquisition",figsize=(10,10))
```

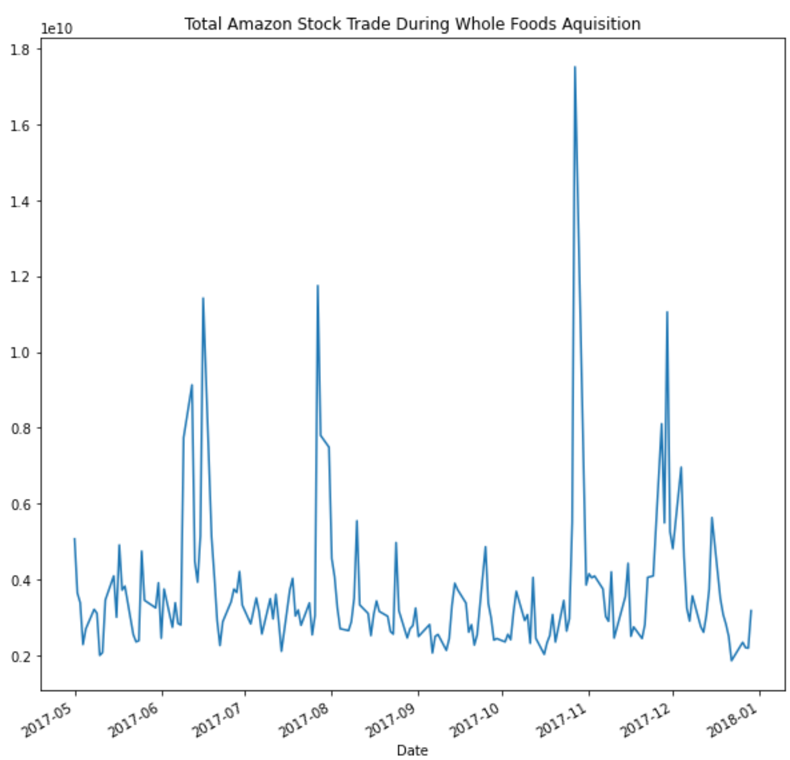
Out[7]:
```
<AxesSubplot:title={'center':'Total Kroger Stock Trade During Ralphs Aquisition'}, xlabel='Date'>
```




We repeated the steps above to generate the total trade of Amazon stock during their Whole Foods acquisition. The manipulation occured on df3.

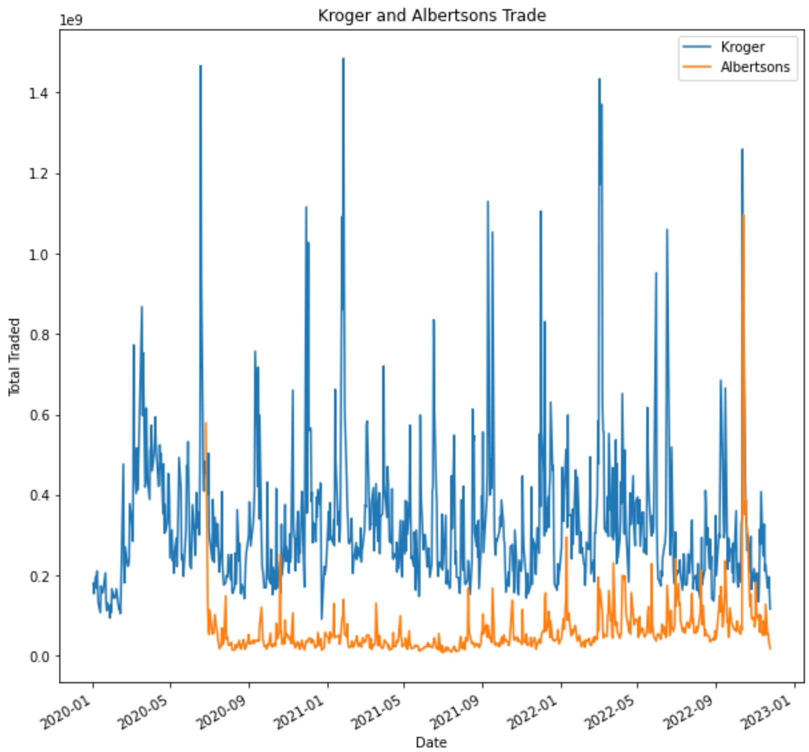
In [8]:
```
df3["Total Traded"] = df3["Open"]*df3["Volume"]
df3["Total Traded"].plot(title="Total Amazon Stock Trade During Whole Foods Aquisition",figsize=(10,10))
```

Out[8]:
```
<AxesSubplot:title={'center':'Total Amazon Stock Trade During Whole Foods Aquisition'}, xlabel='Date'>
```




Finally we used the Kroger and Albertsons data frame to plot trade volume to idenfify a pattern during their acquisition.

In [9]:
```
# Kroger and Albertsons stock trade during aquisition
Kroger["Kroger"] = Kroger["Open"]*Kroger["Volume"]
Albertsons["Albertsons"] = Albertsons["Open"]*Albertsons["Volume"]

Kroger["Kroger"].plot(title="Total Kroger Trade",figsize=(10,10))
Albertsons["Albertsons"].plot(title="Total Albertsons Trade",figsize=(10,10))

plt.legend()
plt.title("Kroger and Albertsons Trade")
plt.ylabel("Total Traded")
plt.show()
```

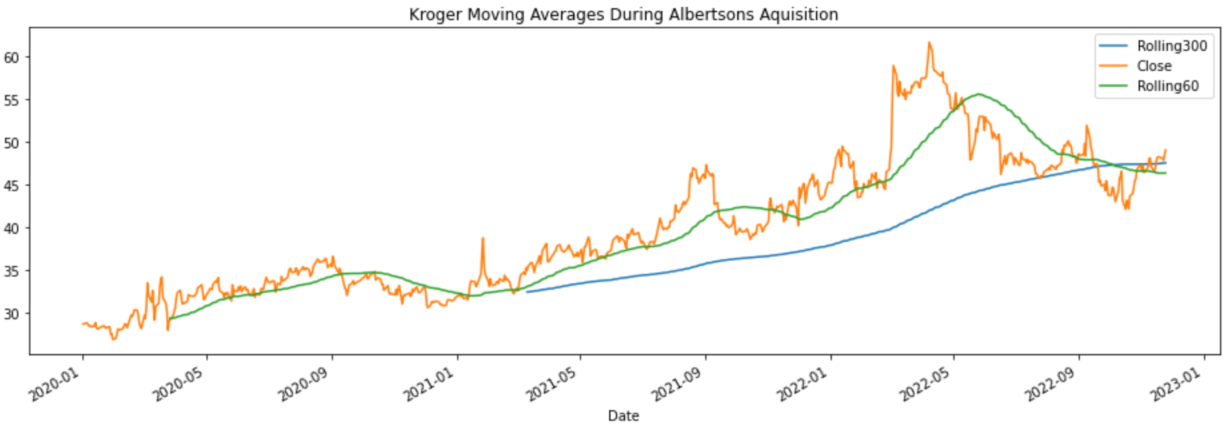



We found that Albertsons and Kroger follow very similar volumes. However, Albertsons has been consitently lower than Kroger. This might point to how the grocery giant was able to buy its competitior. However, the plots suggest high significance of market movement.

The next analysis we conduced was the rolling averages. To do this we created new columns in the Kroger data frame and used the rolling() method on the close column. Then the mean() method was applied. Using the new columns we plotted Rolling 300, close, and Rolling 60.

In [63]:
```
Kroger["Rolling300"]=Kroger["Close"].rolling(300).mean()
Kroger["Rolling300"].plot(figsize=(16,5))
Kroger["Close"].plot()
Kroger["Rolling60"]=Kroger["Close"].rolling(60).mean()
Kroger["Rolling60"].plot()

plt.legend()
plt.title("Kroger Moving Averages During Albertsons Aquisition")
```

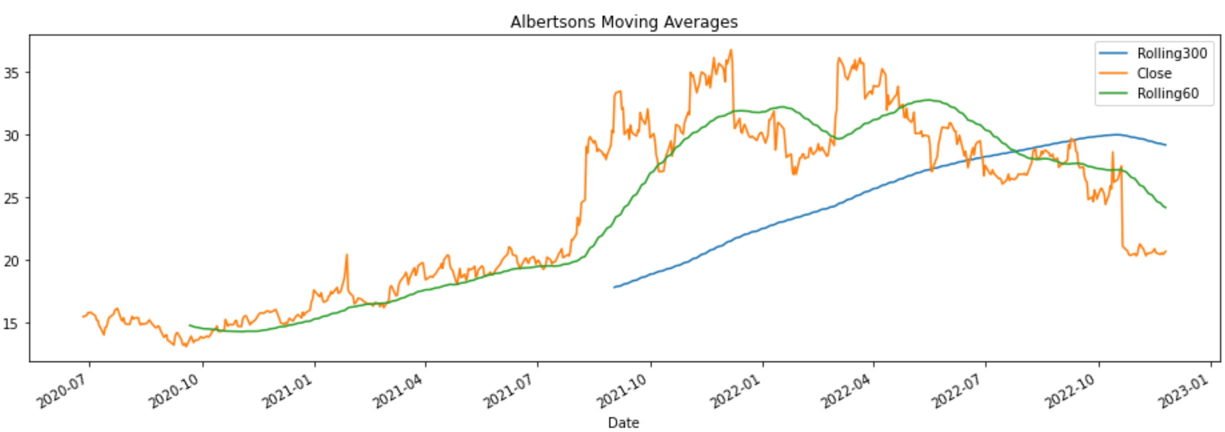
Out[63]: `Text(0.5, 1.0, 'Kroger Moving Averages During Albertsons Aquisition')`




The steps for Kroger where repeated on the Albertsons data frame.

In [11]:
```
Albertsons["Rolling300"]=Albertsons["Close"].rolling(300).mean()
Albertsons["Rolling300"].plot(figsize=(16,5))
Albertsons["Close"].plot()
Albertsons["Rolling60"]=Albertsons["Close"].rolling(60).mean()
Albertsons["Rolling60"].plot()

plt.legend()
plt.title("Albertsons Moving Averages")
```

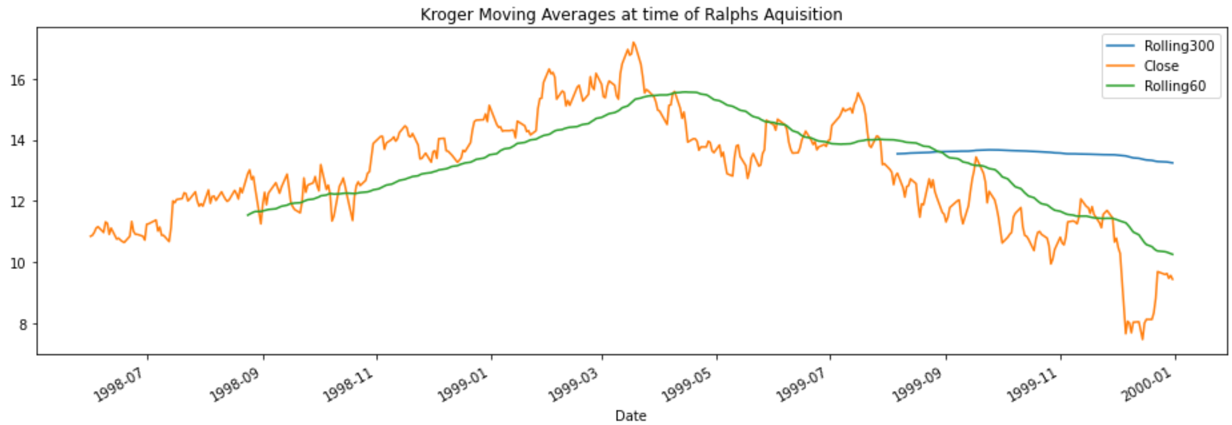
Out[11]: `Text(0.5, 1.0, 'Albertsons Moving Averages')`




Using the data frame (df4) created to analyze Kroger during the Ralphs Acquisition we applied the rolling() method with the same arguments and took the mean to create another plot.

In [12]:
```
df4["Rolling300"]=df4["Close"].rolling(300).mean()
df4["Rolling300"].plot(figsize=(16,5))
df4["Close"].plot()
df4["Rolling60"]=df4["Close"].rolling(60).mean()
df4["Rolling60"].plot()

plt.legend()
plt.title("Kroger Moving Averages at time of Ralphs Aquisition")
```

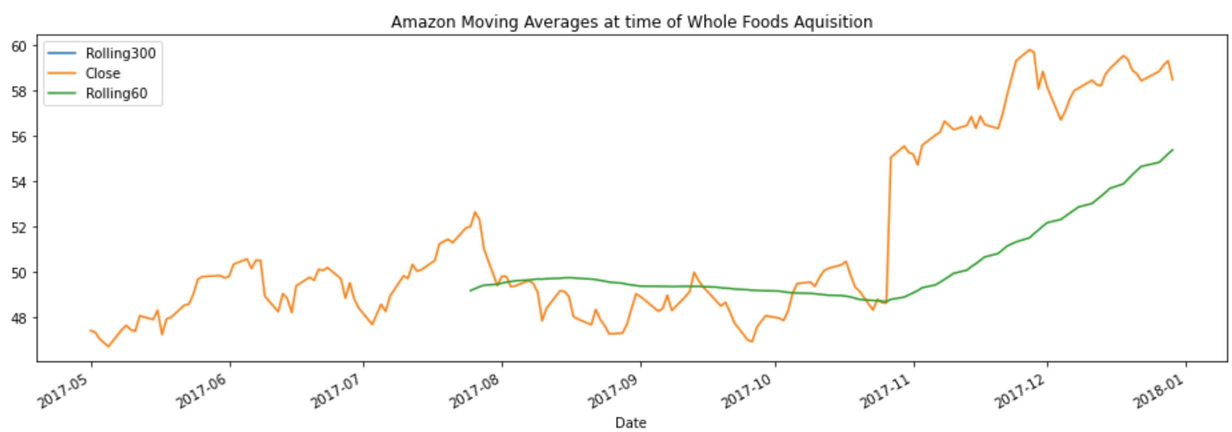
Out[12]:
```
Text(0.5, 1.0, 'Kroger Moving Averages at time of Ralphs Aquisition')
```




We applied the same methods to the Amazon data frame (df3) during the Whole Foods Acquisition.

In [13]:
```
df3["Rolling300"]=df3["Close"].rolling(300).mean()
df3["Rolling300"].plot(figsize=(16,5))
df3["Close"].plot()
df3["Rolling60"]=df3["Close"].rolling(60).mean()
df3["Rolling60"].plot()

plt.legend()
plt.title("Amazon Moving Averages at time of Whole Foods Aquisition")
```

Out[13]:
```
Text(0.5, 1.0, 'Amazon Moving Averages at time of Whole Foods Aquisition')
```

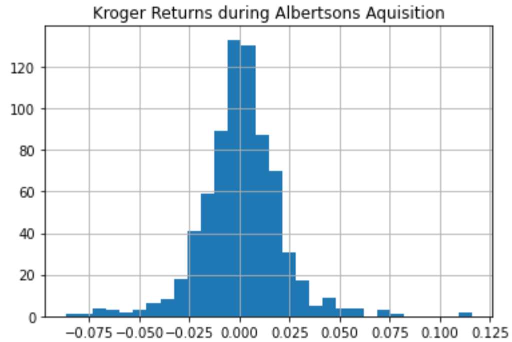



We found that Kroger is likely attempting to recreate the success of the Ralphs acquisition. However, given the success of services such as Amazon it is uncertain if the sucess is replicatable.

The next plots are an analysis of return volatility. This was accomplished by applying the .pct_change() method on the close colunm and creating a new returns column. Then the .hist() method was used. We had to install pylab to add titles to our plots. This manipulation was done to the Kroger data frame, Albertsons data frame, and Kroger during Ralphs data frame(df4).

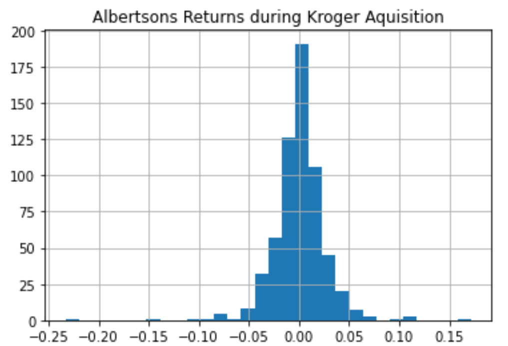
In [62]:
```
Kroger["returns"] = Kroger["Close"].pct_change()
Kroger["returns"].hist(bins=30)
py.title("Kroger Returns during Albertsons Aquisition")
```

Out[62]: Text(0.5, 1.0, 'Kroger Returns during Albertsons Aquisition')



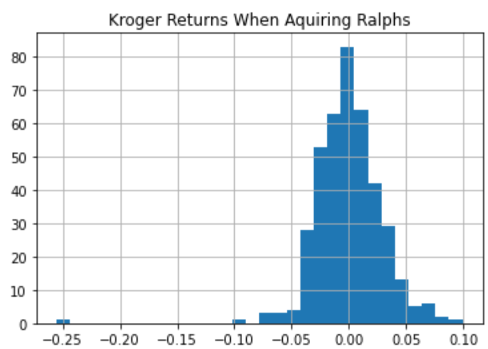

In [60]:
```
Albertsons["returns"] = Albertsons["Close"].pct_change()
Albertsons["returns"].hist(bins=30)
py.title("Albertsons Returns during Kroger Aquisition")
```

Out[60]: Text(0.5, 1.0, 'Albertsons Returns during Kroger Aquisition')




In [59]:
```
#Kroger at time of aquiring raphs
df4["returns"] = df4["Close"].pct_change()
df4["returns"].hist(bins=30)
py.title("Kroger Returns When Aquiring Ralphs")
```

Out[59]: Text(0.5, 1.0, 'Kroger Returns When Aquiring Ralphs')




We found that the Albertsons acquisition was more risky for Kroger. This is also very different from Amazon's acquisition of Whole Foods. This means shareholders might not think the acquisition was a good move.

In order to clean the data we generated by searching the number of store locations we needed a data frame containing all the state ids. The data was taken from https://worldpopulationreview.com/states/state-abbreviations (https://worldpopulationreview.com/states/state-abbreviations). However, not all the data was needed and we had to drop a column from the data frame. Finally, we created a dictionary to iterate over later.

In [18]:
```
states = pd.read_csv("csvData.csv")

states = states.set_index("state")
states = states.drop("abbrev", axis=1)

states = states.to_dict()
```

We created an Albertsons.csv and Kroger.csv with the number of store locations in each state for each respective store.

In [19]:
```
alb = pd.read_csv('Albertsons.csv')
alb
```

Out[19]:

| | State | Number of Stores |
|---|---|---|
| 0 | Arizona | 30 |
| 1 | Arkansas | 1 |
| 2 | California | 125 |
| 3 | Colorado | 2 |
| 4 | Idaho | 39 |
| 5 | Louisiana | 16 |
| 6 | Motana | 29 |
| 7 | Nevada | 35 |
| 8 | New Mexico | 6 |
| 9 | North Dakota | 1 |
| 10 | Oregon | 29 |
| 11 | Texas | 43 |
| 12 | Utah | 2 |
| 13 | Washington | 19 |
| 14 | Wyoming | 9 |

In order to create the choropleths we needed to use state ids to call the function, therefore, in each data frame we created an empty column called ids using a lambda function.

In [20]:
```
alb["ids"]=alb.apply(lambda _:"",axis=1)
alb
```

Out[20]:

| | State | Number of Stores | ids |
|---|---|---|---|
| 0 | Arizona | 30 | |
| 1 | Arkansas | 1 | |
| 2 | California | 125 | |
| 3 | Colorado | 2 | |
| 4 | Idaho | 39 | |
| 5 | Louisiana | 16 | |
| 6 | Motana | 29 | |
| 7 | Nevada | 35 | |
| 8 | New Mexico | 6 | |
| 9 | North Dakota | 1 | |
| 10 | Oregon | 29 | |
| 11 | Texas | 43 | |
| 12 | Utah | 2 | |
| 13 | Washington | 19 | |
| 14 | Wyoming | 9 | |

This is the Kroger.csv data frame (kro). The same methods were done to it as the Albertsons data frame.

In [21]:
```
kro = pd.read_csv('Kroger.csv')
kro
```

Out[21]:

| | State | Number of stores |
|---|---|---|
| 0 | Alabama | 10 |
| 1 | Arkansas | 26 |
| 2 | Georgia | 167 |
| 3 | Illinois | 30 |
| 4 | Indiana | 103 |
| 5 | Kentucky | 104 |
| 6 | Louisiana | 8 |
| 7 | Michigan | 120 |
| 8 | Missouri | 3 |
| 9 | Mississippi | 29 |
| 10 | Ohio | 196 |
| 11 | South Carolina | 13 |
| 12 | Tennessee | 115 |
| 13 | Texas | 209 |
| 14 | Virgina | 68 |
| 15 | West Virgina | 38 |

In [22]:
```
kro["ids"]=kro.apply(lambda _:"",axis=1)
kro
```

Out[22]:

| | State | Number of stores | ids |
|---|---|---|---|
| 0 | Alabama | 10 | |
| 1 | Arkansas | 26 | |
| 2 | Georgia | 167 | |
| 3 | Illinois | 30 | |
| 4 | Indiana | 103 | |
| 5 | Kentucky | 104 | |
| 6 | Louisiana | 8 | |
| 7 | Michigan | 120 | |
| 8 | Missouri | 3 | |
| 9 | Mississippi | 29 | |
| 10 | Ohio | 196 | |
| 11 | South Carolina | 13 | |
| 12 | Tennessee | 115 | |
| 13 | Texas | 209 | |
| 14 | Virgina | 68 | |
| 15 | West Virgina | 38 | |

Unfortunatly, some of the state names where misspelled. So we used the .loc function to correct the data.

In [27]:
```
#Virginia is misplelled so I needed to fix it
kro.loc[kro["State"]=="West Virgina","State"]="West Virginia"
kro.loc[kro["State"]=="Virgina","State"]="Virginia"
alb.loc[alb["State"]=="Motana","State"]="Montana"
```

We created a new dictionary; since, states was a nested dictionary. Then we iterated over the dictionary and checked if a key was in each data frame. If it is the data frame's ids column is updated with the state id.

In [28]:
```
s = states["code"]

for k, v in s.items():
    if k in alb.State.values:
        alb.loc[alb["State"]==k,"ids"]=v
    if k in kro.State.values:
        kro.loc[kro["State"]==k,"ids"]=v
alb
```

Out[28]:

| | State | Number of Stores | ids |
|---|---|---|---|
| **0** | Arizona | 30 | AZ |
| **1** | Arkansas | 1 | AR |
| **2** | California | 125 | CA |
| **3** | Colorado | 2 | CO |
| **4** | Idaho | 39 | ID |
| **5** | Louisiana | 16 | LA |
| **6** | Montana | 29 | MT |
| **7** | Nevada | 35 | NV |
| **8** | New Mexico | 6 | NM |
| **9** | North Dakota | 1 | ND |
| **10** | Oregon | 29 | OR |
| **11** | Texas | 43 | TX |
| **12** | Utah | 2 | UT |
| **13** | Washington | 19 | WA |
| **14** | Wyoming | 9 | WY |

Using the plotly.express we created choropleth with the cleaned data from the alb and kro data frames. Using the ids column as a key and heat colors to show the intensity of the number of stores. The data came from https://www.scrapehero.com/location-reports/Albertsons-USA/ (https://www.scrapehero.com/location-reports/Albertsons-USA/) and https://www.scrapehero.com/kroger-store-locations/ (https://www.scrapehero.com/kroger-store-locations/)

In [40]:
```
fig = px.choropleth(alb, locations="ids",locationmode="USA-states", scope="usa",
                    color="Number of Stores",color_continuous_scale="plasma",
                    title="No. Albertsons Locations")

fig.show()
```

In [41]:
```
fig = px.choropleth(kro, locations="ids",locationmode="USA-states", scope="usa",
                    color="Number of stores",color_continuous_scale="plasma",
                   title="No. Kroger Locations")

fig.show()
```

We found that Kroger likely used the acquisition to expand their reach into the western United States.

The following is a data frame we created from company balance sheets. They have quartly revenues from 2018 onwards.

In [17]:
```
reven = pd.read_excel('172- revenue.xlsx')
reven
```

Out[17]:

| | Revenue | Kroger | Albertsons | Walmart | Costco |
|---|---|---|---|---|---|
| **0** | (Millions of US $) | NaN | NaN | NaN | NaN |
| **1** | 2018 Q1 | 31649.0 | NaN | 136267.0 | 32995.0 |
| **2** | 2018 Q2 | 37722.0 | NaN | 122690.0 | 32361.0 |
| **3** | 2018 Q3 | 28014.0 | NaN | 128028.0 | 44411.0 |
| **4** | 2018 Q4 | 27831.0 | NaN | 124894.0 | 35069.0 |
| **5** | 2019 Q1 | 28285.0 | NaN | 138793.0 | 35396.0 |
| **6** | 2019 Q2 | 37251.0 | 18738.0 | 123925.0 | 34740.0 |
| **7** | 2019 Q3 | 28168.0 | 14177.0 | 130377.0 | 47498.0 |
| **8** | 2019 Q4 | 27974.0 | 14103.0 | 127991.0 | 37040.0 |
| **9** | 2020 Q1 | 28893.0 | 15437.0 | 141671.0 | 39072.0 |
| **10** | 2020 Q2 | 41549.0 | 22752.0 | 134622.0 | 37266.0 |
| **11** | 2020 Q3 | 30489.0 | 15758.0 | 137742.0 | 53383.0 |
| **12** | 2020 Q4 | 29723.0 | 15409.0 | 134708.0 | 43208.0 |
| **13** | 2021 Q1 | 30737.0 | 15772.0 | 152079.0 | 44769.0 |
| **14** | 2021 Q2 | 41298.0 | 21269.0 | 138310.0 | 45277.0 |
| **15** | 2021 Q3 | 31682.0 | 16506.0 | 141048.0 | 62675.0 |
| **16** | 2021 Q4 | 31860.0 | 16728.0 | 140525.0 | 50363.0 |
| **17** | 2022 Q1 | 33048.0 | 17384.0 | 152871.0 | 51904.0 |
| **18** | 2022 Q2 | 44600.0 | 23310.0 | 141569.0 | 52596.0 |
| **19** | 2022 Q3 | 34638.0 | 17919.0 | 152859.0 | 72091.0 |

We needed to clean the reven data frame generated earlier. Therefore, we set the quarters to be the index and deleted the first row. The first row did not have relevent data. This was accomplished using the .set_index() method and .iloc method.

In [31]:
```
reven
reven = reven.set_index("Revenue")
reven = reven.iloc[1: , :]
reven
```

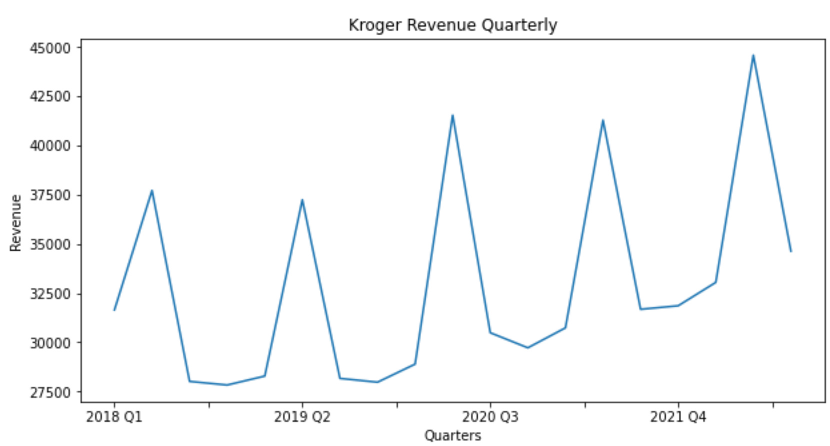
Out[31]:

| Revenue | Kroger | Albertsons | Walmart | Costco |
|---|---|---|---|---|
| **2018 Q1** | 31649.0 | NaN | 136267.0 | 32995.0 |
| **2018 Q2** | 37722.0 | NaN | 122690.0 | 32361.0 |
| **2018 Q3** | 28014.0 | NaN | 128028.0 | 44411.0 |
| **2018 Q4** | 27831.0 | NaN | 124894.0 | 35069.0 |
| **2019 Q1** | 28285.0 | NaN | 138793.0 | 35396.0 |
| **2019 Q2** | 37251.0 | 18738.0 | 123925.0 | 34740.0 |
| **2019 Q3** | 28168.0 | 14177.0 | 130377.0 | 47498.0 |
| **2019 Q4** | 27974.0 | 14103.0 | 127991.0 | 37040.0 |
| **2020 Q1** | 28893.0 | 15437.0 | 141671.0 | 39072.0 |
| **2020 Q2** | 41549.0 | 22752.0 | 134622.0 | 37266.0 |
| **2020 Q3** | 30489.0 | 15758.0 | 137742.0 | 53383.0 |
| **2020 Q4** | 29723.0 | 15409.0 | 134708.0 | 43208.0 |
| **2021 Q1** | 30737.0 | 15772.0 | 152079.0 | 44769.0 |
| **2021 Q2** | 41298.0 | 21269.0 | 138310.0 | 45277.0 |
| **2021 Q3** | 31682.0 | 16506.0 | 141048.0 | 62675.0 |
| **2021 Q4** | 31860.0 | 16728.0 | 140525.0 | 50363.0 |
| **2022 Q1** | 33048.0 | 17384.0 | 152871.0 | 51904.0 |
| **2022 Q2** | 44600.0 | 23310.0 | 141569.0 | 52596.0 |
| **2022 Q3** | 34638.0 | 17919.0 | 152859.0 | 72091.0 |

The following plots where created by creating new data frames with only a column of interest using the .loc function. The plots show quarterly revenues.

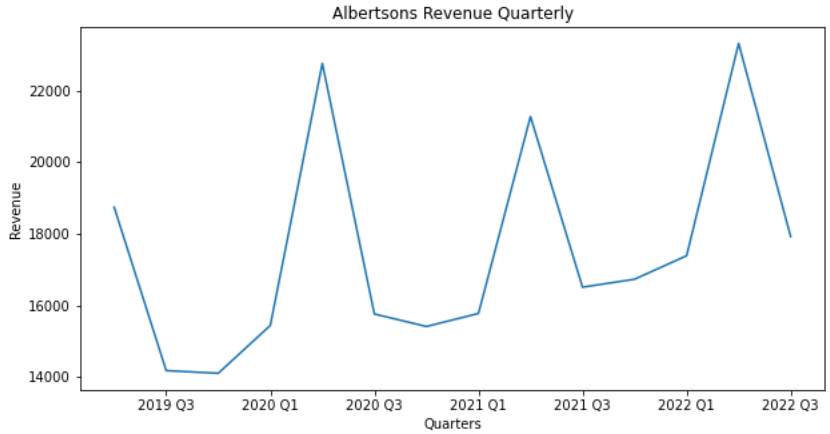
In [49]:
```
kroger = reven.loc[:,"Kroger"]
k = kroger.plot(figsize=(10,5),title="Kroger Revenue Quarterly",)
k.set_xlabel("Quarters")
k.set_ylabel("Revenue")
```

Out[49]: `Text(0, 0.5, 'Revenue')`



In [51]:
```
albert = reven.loc[:,"Albertsons"]
a=albert.plot(figsize=(10,5),title="Albertsons Revenue Quarterly")
a.set_xlabel("Quarters")
a.set_ylabel("Revenue")
```

Out[51]: Text(0, 0.5, 'Revenue')

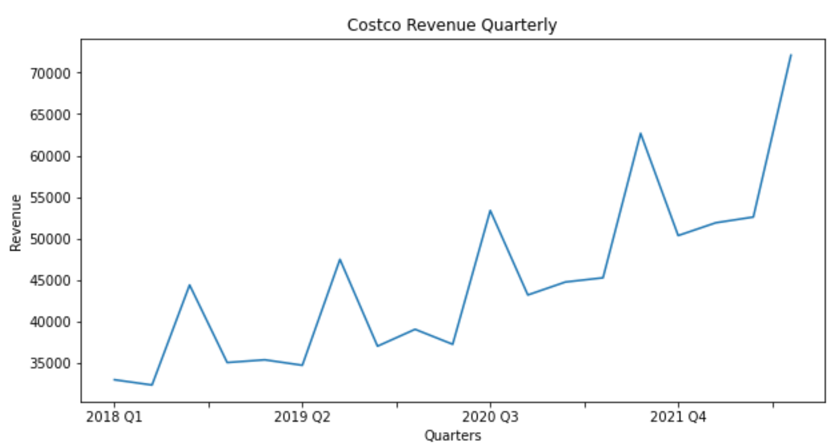



In [52]:
```
walt = reven.loc[:,"Walmart"]
w=walt.plot(figsize=(10,5),title="Walmart Revenue Quarterly")
w.set_xlabel("Quarters")
w.set_ylabel("Revenue")
```

Out[52]: Text(0, 0.5, 'Revenue')


In [53]:
```
cost = reven.loc[:,"Costco"]
c=cost.plot(figsize=(10,5),title="Costco Revenue Quarterly")
c.set_xlabel("Quarters")
c.set_ylabel("Revenue")
```

Out[53]: Text(0, 0.5, 'Revenue')



We found the peakyness of the data to be very interesting. Additionally, all of the companies show a general upward trend. Therefore, Kroger might have purchased Albertsons to boost revenues. However, Kroger might struggle to remain profitable against major competitors such as Walmart and Costco.