Import Necessary Libraries

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns

df=pd.read_csv("Walmart.csv")
df.head()
```

```
   Store        Date  Weekly_Sales  Holiday_Flag  Temperature
Fuel_Price  \
0      1  05-02-2010    1643690.90             0        42.31
2.572
1      1  12-02-2010    1641957.44             1        38.51
2.548
2      1  19-02-2010    1611968.17             0        39.93
2.514
3      1  26-02-2010    1409727.59             0        46.63
2.561
4      1  05-03-2010    1554806.68             0        46.50
2.625

          CPI  Unemployment
0  211.096358         8.106
1  211.242170         8.106
2  211.289143         8.106
3  211.319643         8.106
4  211.350143         8.106
```

```
df.info()
```

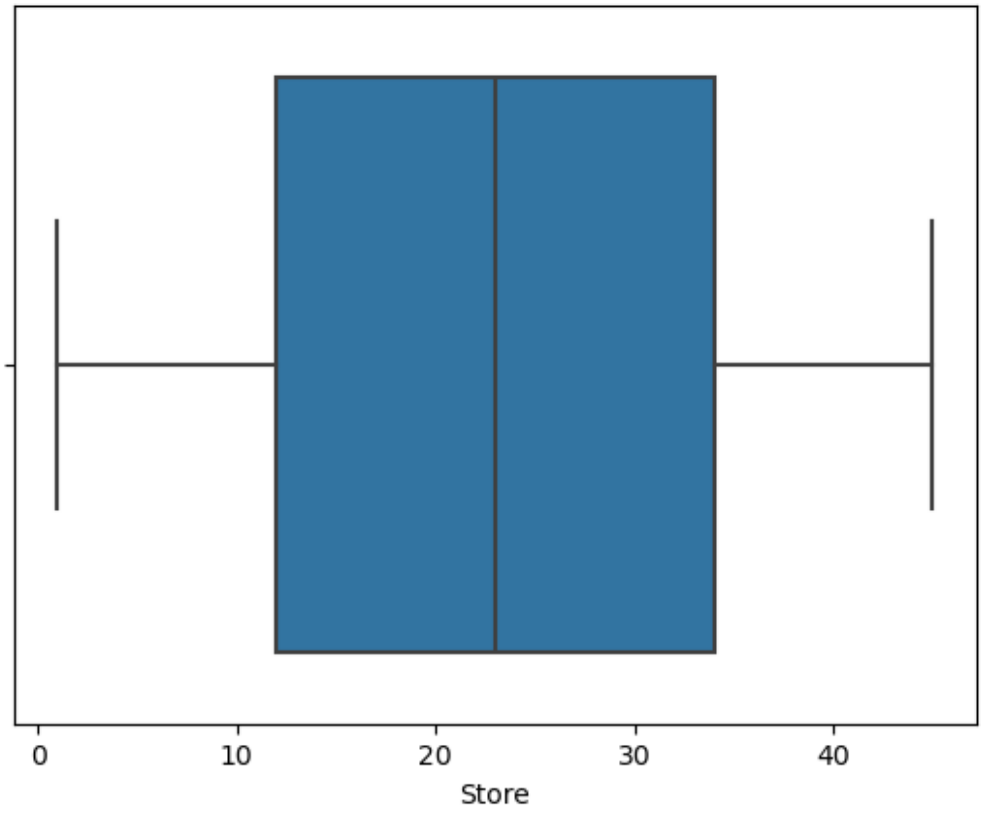
```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 6435 entries, 0 to 6434
Data columns (total 8 columns):
 #   Column        Non-Null Count  Dtype
---  ------        --------------  -----
 0   Store         6435 non-null   int64
 1   Date          6435 non-null   object
 2   Weekly_Sales  6435 non-null   float64
 3   Holiday_Flag  6435 non-null   int64
 4   Temperature   6435 non-null   float64
 5   Fuel_Price    6435 non-null   float64
 6   CPI           6435 non-null   float64
 7   Unemployment  6435 non-null   float64
dtypes: float64(5), int64(2), object(1)
memory usage: 402.3+ KB
```

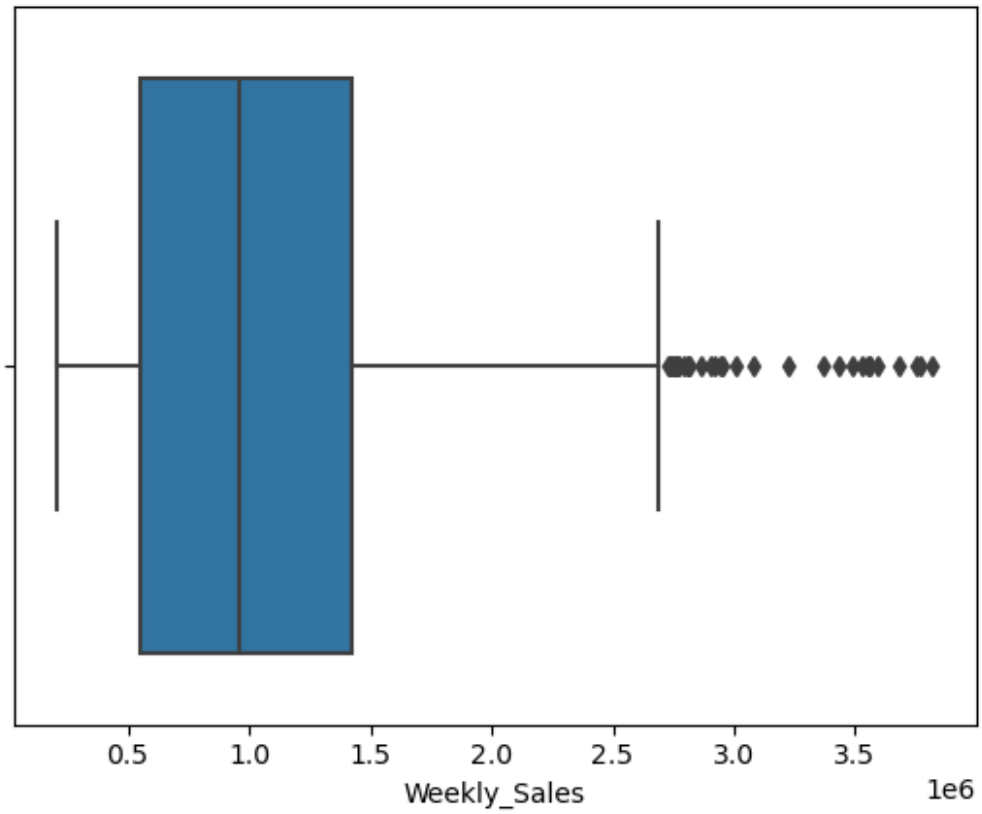
```
df.isnull().sum()  # checking null values
```

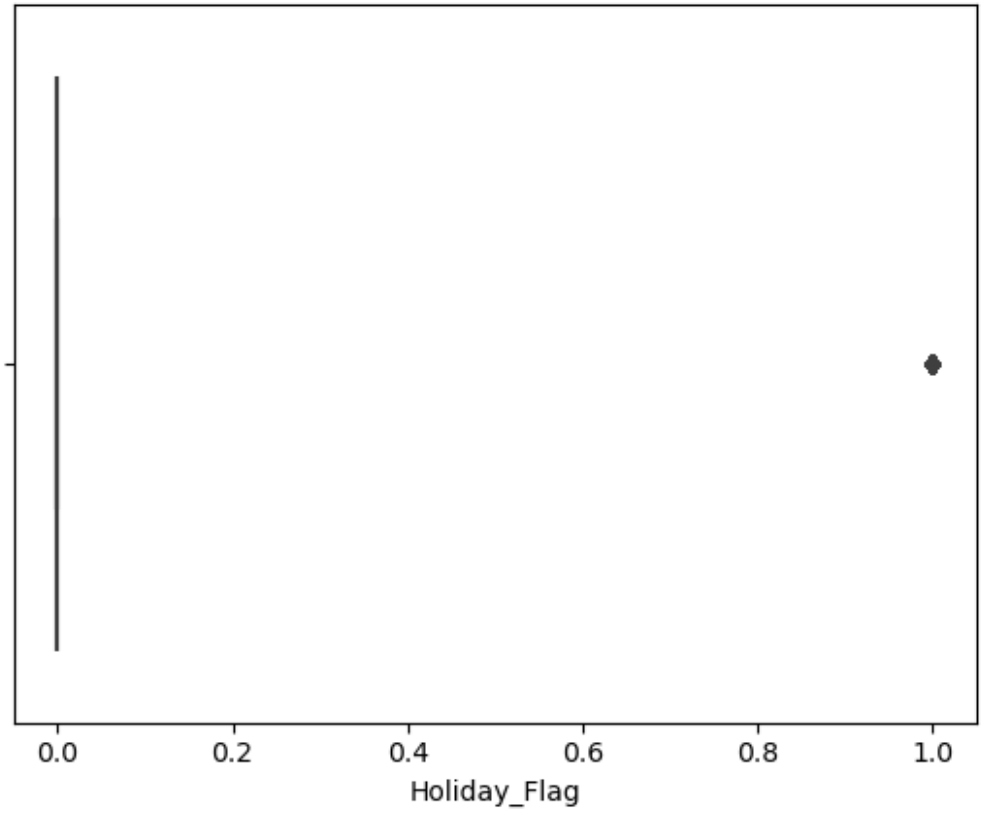
```
Store           0
Date            0
Weekly_Sales    0
Holiday_Flag    0
Temperature     0
Fuel_Price      0
CPI             0
Unemployment    0
dtype: int64
```

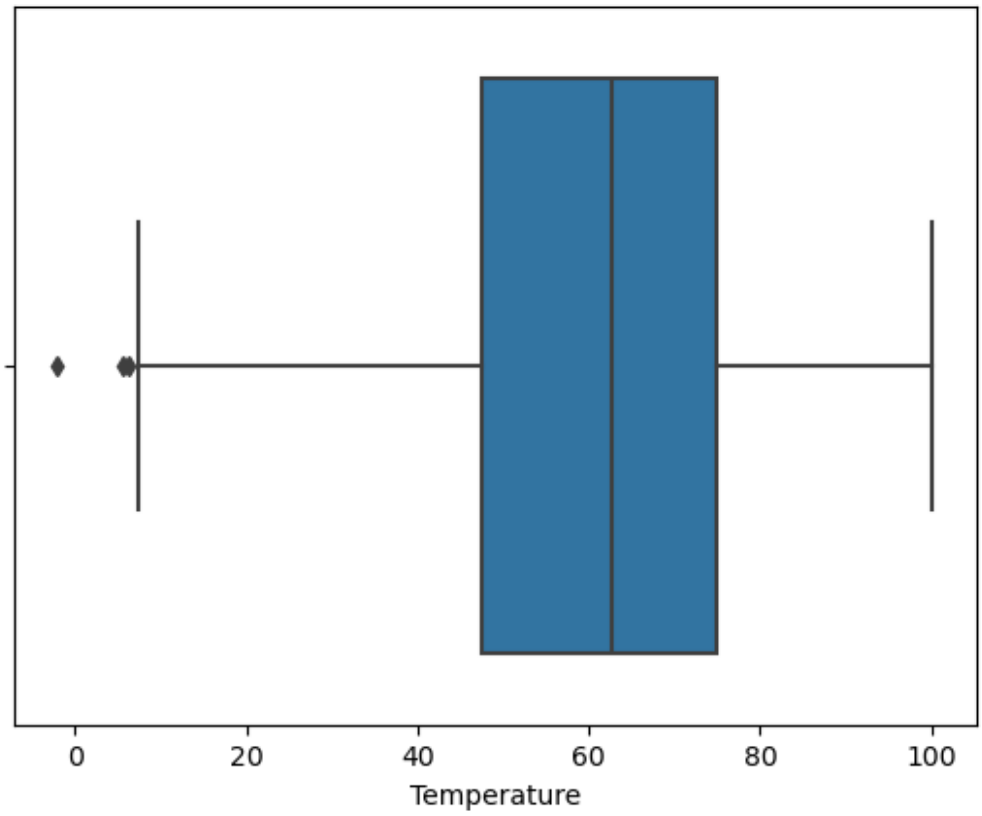
CHECKING FOR OUTLIERS

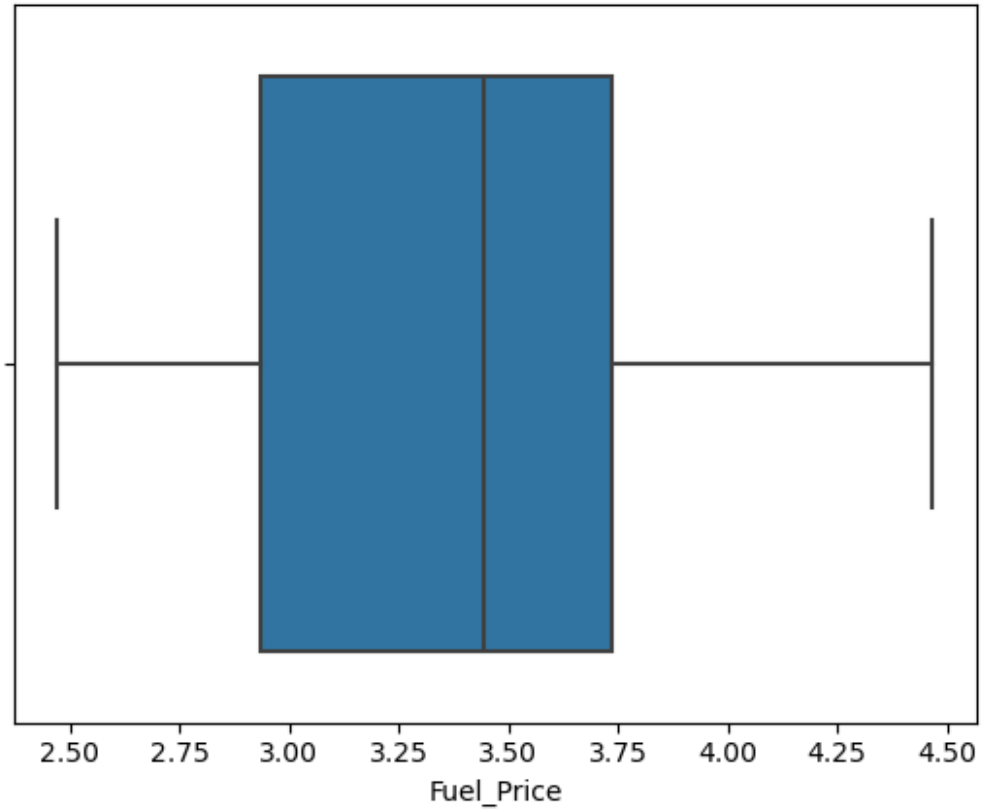
```
column_list = df.columns

for i in column_list:
    if df.dtypes[i]=='int64' or df.dtypes[i]=='float64':
        sns.boxplot(x=df[i])
        plt.show()
```

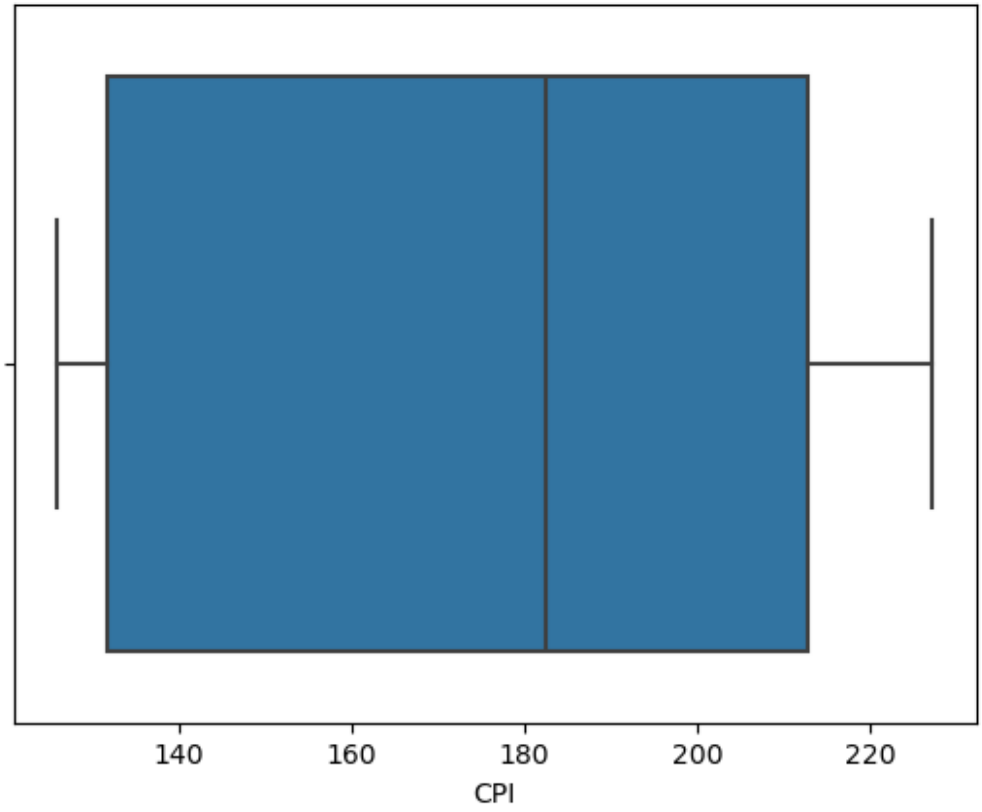


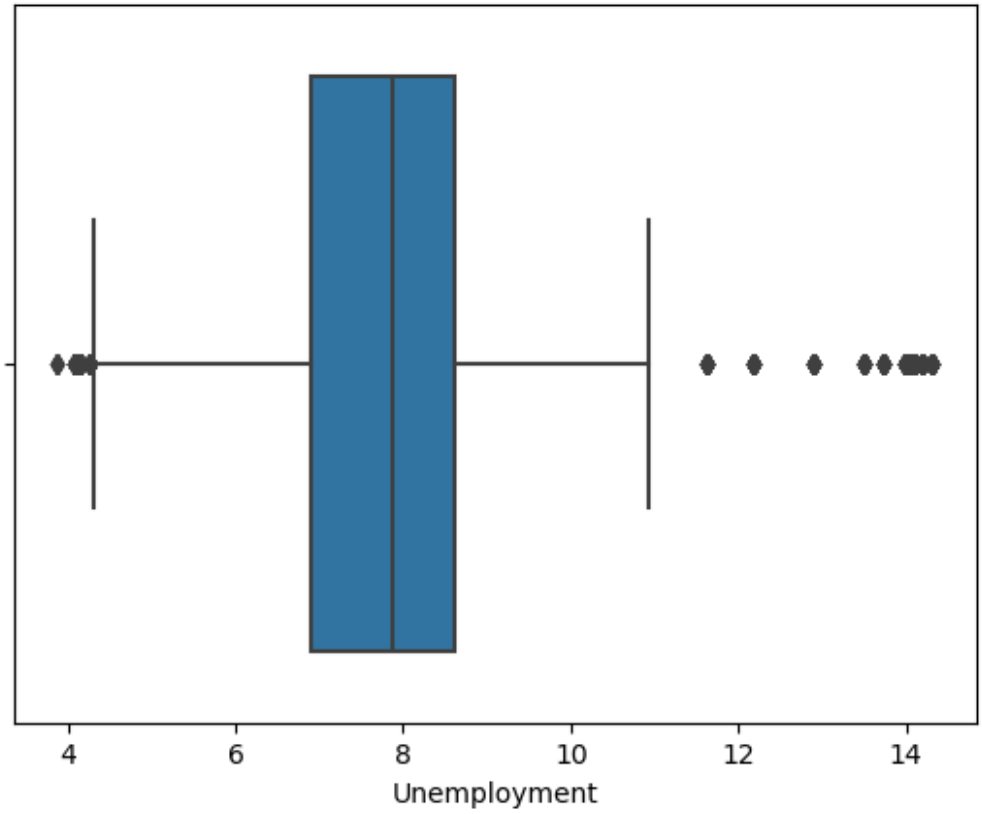

0.5
1.0
1.5
2.0
2.5
3.0
3.5
Weekly_Sales
1e6


0.0
0.2
0.4
0.6
0.8
1.0
Holiday_Flag


0
20
40
60
80
100
Temperature


2.50
2.75
3.00
3.25
3.50
3.75
4.00
4.25
4.50
Fuel_Price


140
160
180
200
220
CPI


4
6
8
10
12
14
Unemployment

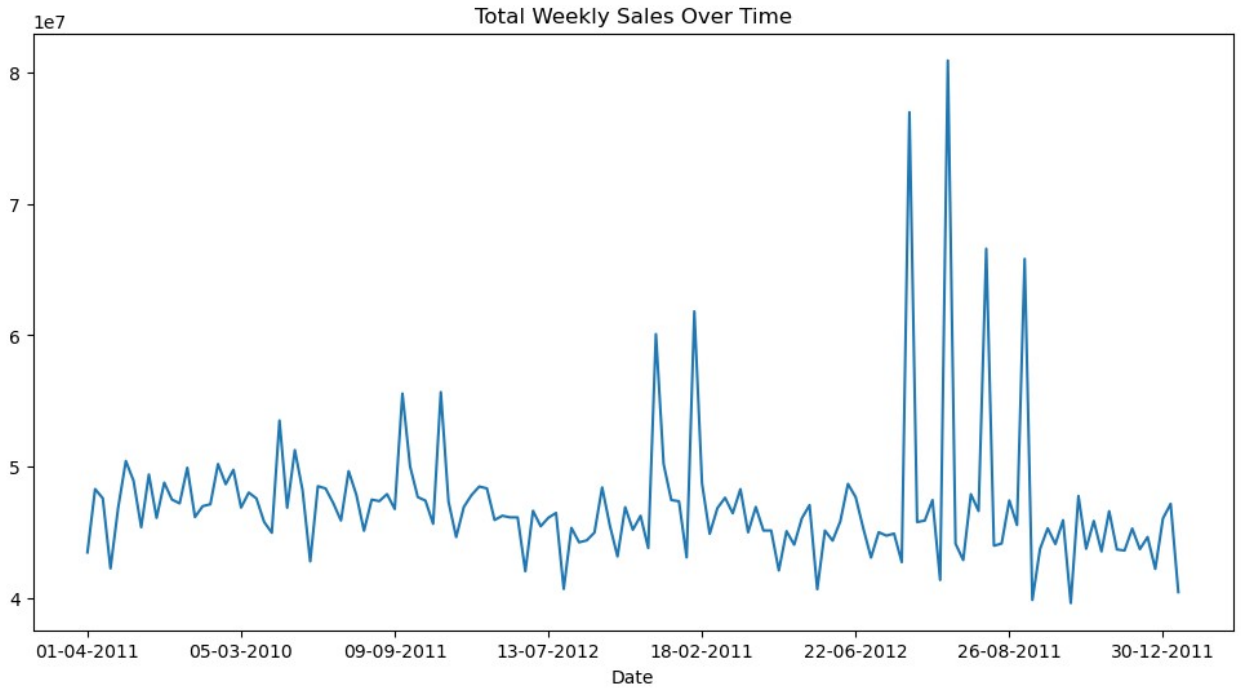
From the above boxplots,it's clear that Weekly_Sales and Unemploment have outliers.

```
# Summary statistics
print(df.describe())
```

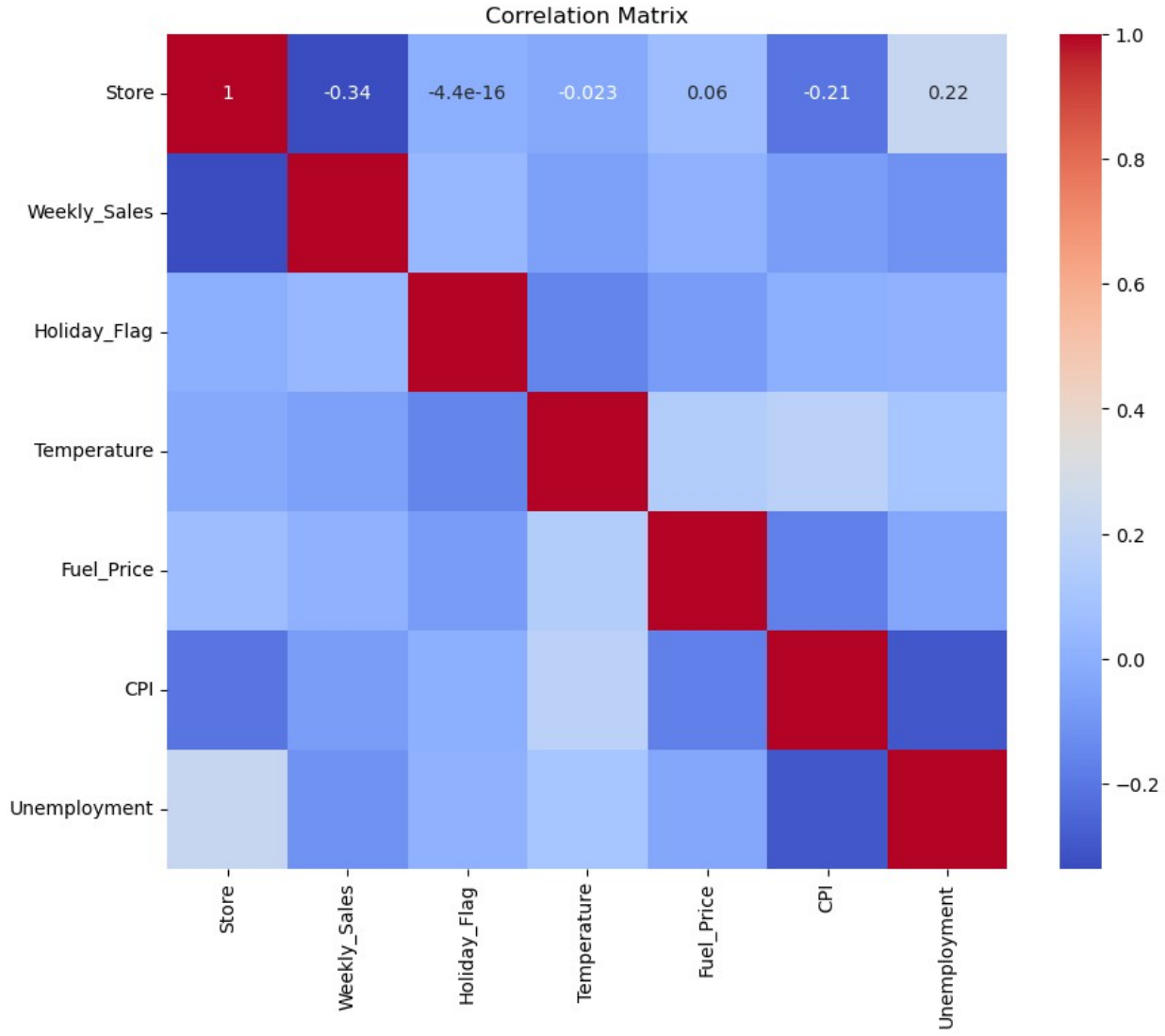
```
              Store  Weekly_Sales  Holiday_Flag  Temperature
Fuel_Price  \
count  6435.000000  6.435000e+03   6435.000000  6435.000000
6435.000000
mean     23.000000  1.046965e+06      0.069930    60.663782
3.358607
std      12.988182  5.643666e+05      0.255049    18.444933
0.459020
min       1.000000  2.099862e+05      0.000000    -2.060000
2.472000
25%      12.000000  5.533501e+05      0.000000    47.460000
2.933000
50%      23.000000  9.607460e+05      0.000000    62.670000
3.445000
75%      34.000000  1.420159e+06      0.000000    74.940000
3.735000
max      45.000000  3.818686e+06      1.000000   100.140000
4.468000

                CPI  Unemployment
count  6435.000000   6435.000000
mean    171.578394      7.999151
std      39.356712      1.875885
min     126.064000      3.879000
25%     131.735000      6.891000
50%     182.616521      7.874000
75%     212.743293      8.622000
max     227.232807     14.313000
```

```
# Time series plot of sales
df.groupby('Date')['Weekly_Sales'].sum().plot(figsize=(12,6),
title='Total Weekly Sales Over Time')
```

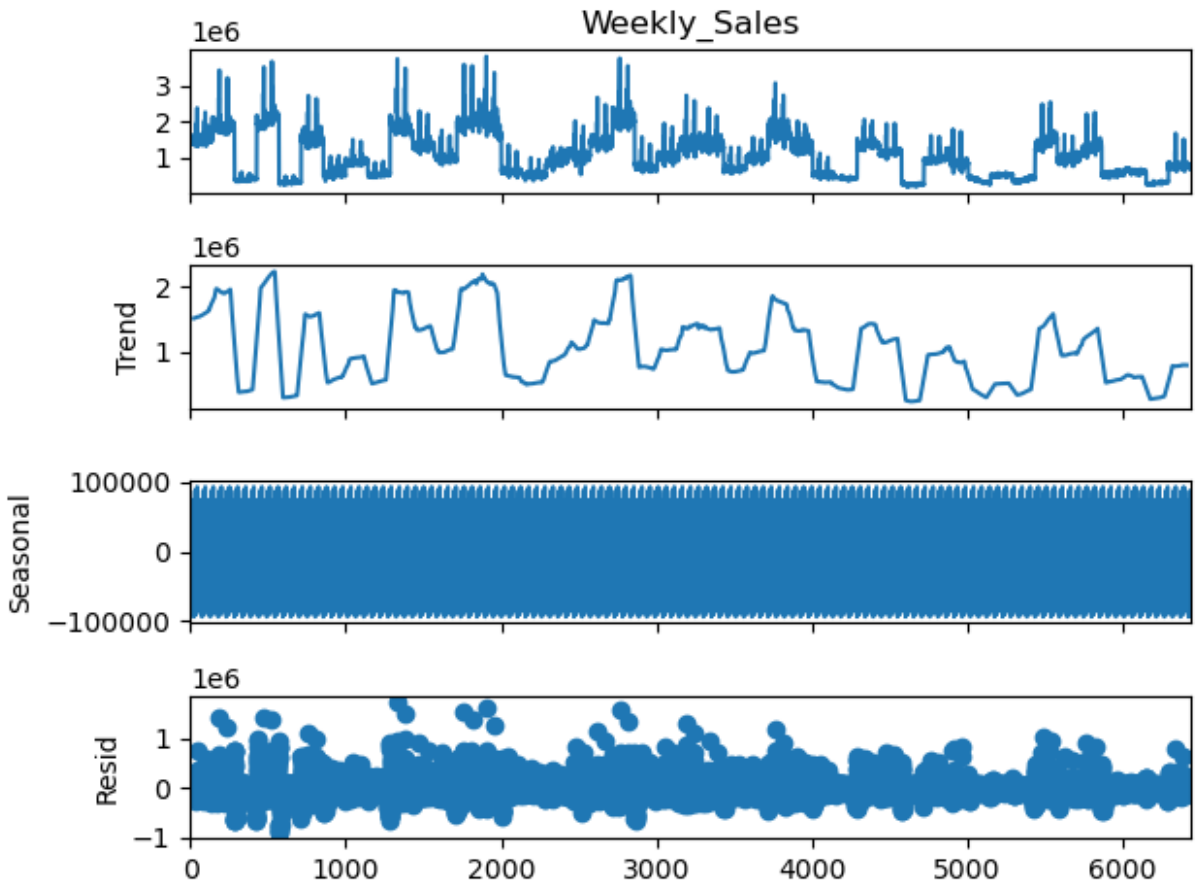
```
<Axes: title={'center': 'Total Weekly Sales Over Time'},
xlabel='Date'>
```

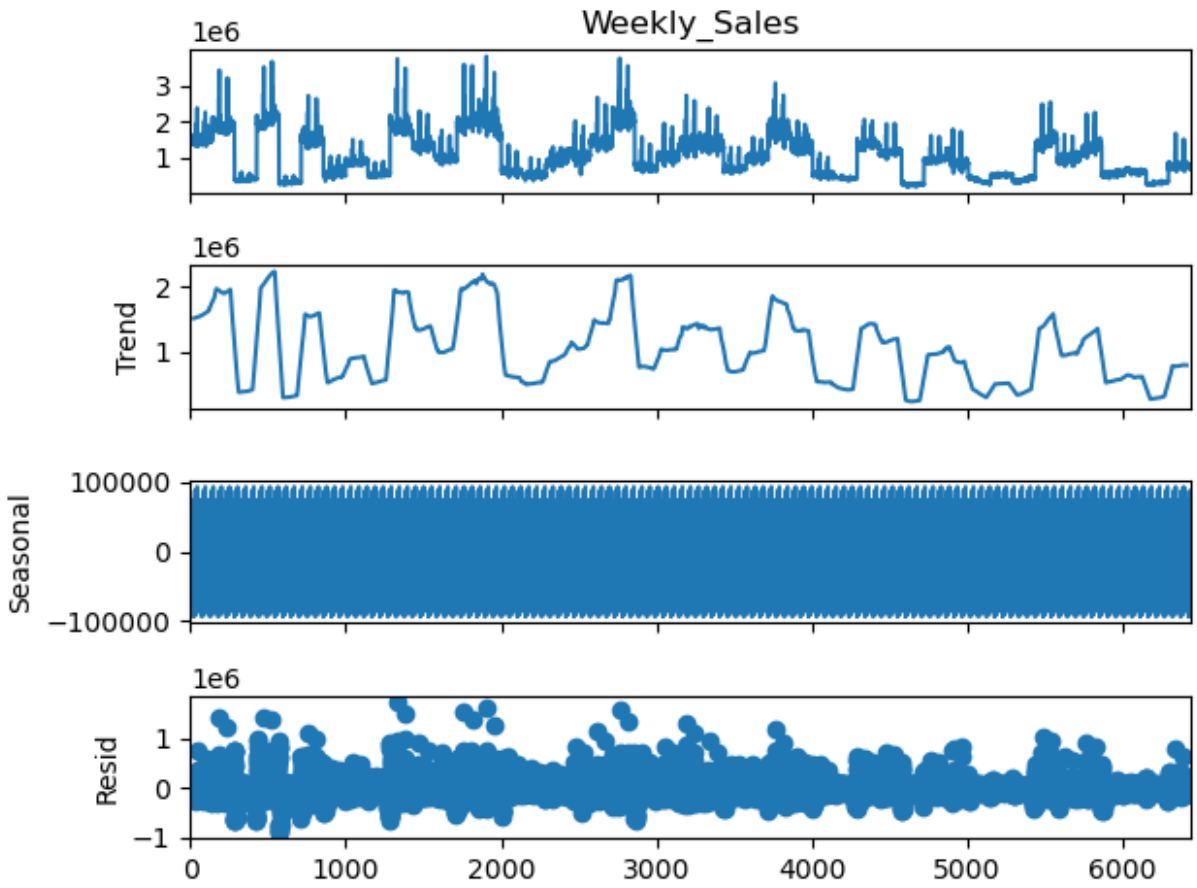



```
# Select only numeric columns for correlation
numeric_df = df.select_dtypes(include=['float64', 'int64'])

# Correlation analysis
correlation = numeric_df.corr()

# Plot the heatmap
plt.figure(figsize=(10, 8))
sns.heatmap(correlation, annot=True, cmap='coolwarm')
plt.title('Correlation Matrix')
plt.show()
```




```
# Seasonal decomposition
from statsmodels.tsa.seasonal import seasonal_decompose
decomposition = seasonal_decompose(df['Weekly_Sales'],
model='additive', period=52)
decomposition.plot()
```


Weekly_Sales
1e6
3
2
1
1e6
Trend
2
1
Seasonal
100000
0
−100000
1e6
Resid
1
0
−1
0
1000
2000
3000
4000
5000
6000




```
store_sales_unemployment = df.groupby('Store')
[['Weekly_Sales','Unemployment']].corr().unstack().iloc[:,1] # group
data by store
print(store_sales_unemployment)
```

```
Store
1    -0.097955
2     0.066325
3    -0.230413
4    -0.337015
5    -0.207043
6     0.044251
7    -0.165382
8    -0.052580
9    -0.191534
10    0.131908
11   -0.020339
12   -0.009286
13   -0.171633
14    0.210786
15    0.078905
16   -0.070864
```

```
17   -0.263600
18    0.139179
19    0.101464
20   -0.095341
21    0.218367
22    0.039043
23   -0.077169
24   -0.012261
25   -0.004958
26   -0.066899
27   -0.014275
28    0.136671
29    0.084682
30    0.201862
31   -0.064738
32   -0.099455
33    0.101175
34    0.017010
35    0.483865
36    0.833734
37   -0.221287
38   -0.785290
39   -0.384681
40   -0.112528
41   -0.350630
42   -0.356355
43   -0.201954
44   -0.780076
45   -0.004041
Name: (Weekly_Sales, Unemployment), dtype: float64
```

```python
from sklearn.linear_model import LinearRegression
import numpy as np

# Function to run linear regression for each store
def linear_regression_per_store(df):
    store_impacts = []

    for store in df['Store'].unique():
        # Filter the data for each store
        store_data = df[df['Store'] == store]

        # Reshape the unemployment data for regression
        X = store_data['Unemployment'].values.reshape(-1, 1)  # 
Independent variable (Unemployment)
        y = store_data['Weekly_Sales'].values  # Dependent variable 
(Weekly Sales)

        # Fit a linear regression model
        model = LinearRegression()
```

```
        model.fit(X, y)

        # Get the slope (coefficient) and intercept
        slope = model.coef_[0]
        intercept = model.intercept_
        store_impacts.append((store, slope))

    # Convert to DataFrame
    store_impacts_df = pd.DataFrame(store_impacts, columns=['Store',
'Impact of Unemployment on Sales'])

    return store_impacts_df

# Run the regression and get the impact of unemployment on sales
impact_df = linear_regression_per_store(df)

# Display the stores where unemployment has the most negative impact
on sales
worst_affected_stores = impact_df.sort_values(by='Impact of
Unemployment on Sales').head()
print(worst_affected_stores)
```

```
    Store  Impact of Unemployment on Sales
40     41                   -166181.375633
38     39                   -119050.372488
16     17                    -90832.279462
19     20                    -86225.540313
3       4                    -63122.487555
```

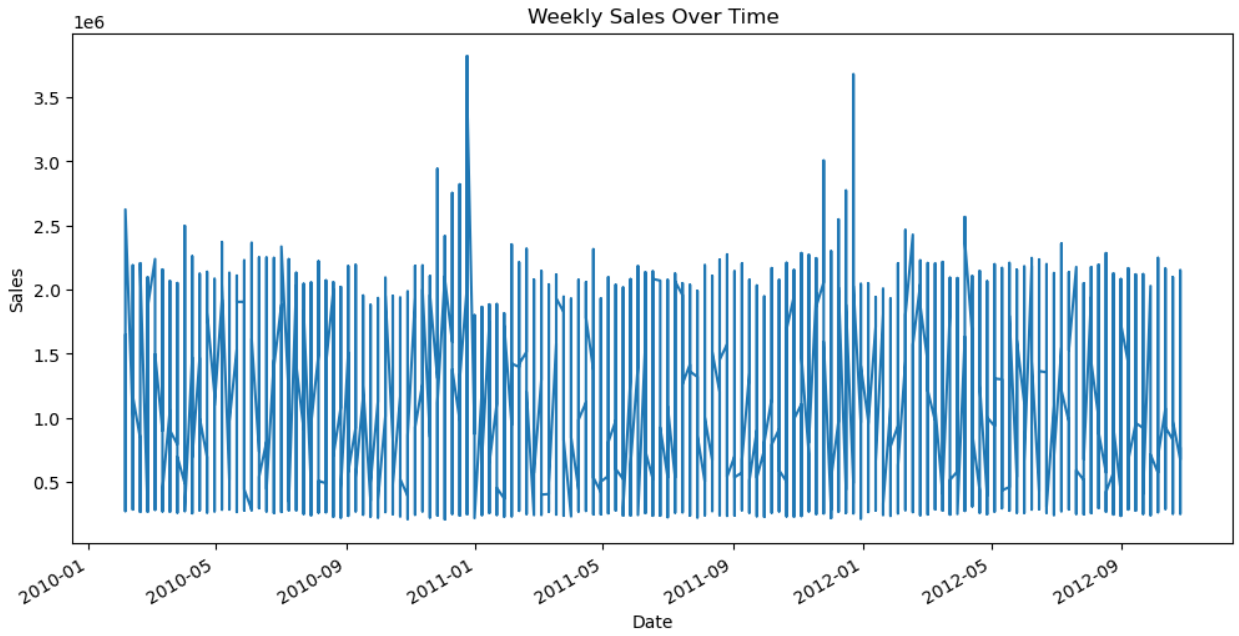
```
df.head()
```

```
   Store        Date  Weekly_Sales  Holiday_Flag  Temperature
Fuel_Price  \
0      1  05-02-2010    1643690.90             0        42.31
2.572
1      1  12-02-2010    1641957.44             1        38.51
2.548
2      1  19-02-2010    1611968.17             0        39.93
2.514
3      1  26-02-2010    1409727.59             0        46.63
2.561
4      1  05-03-2010    1554806.68             0        46.50
2.625

          CPI  Unemployment
0  211.096358         8.106
1  211.242170         8.106
2  211.289143         8.106
3  211.319643         8.106
4  211.350143         8.106
```

```
df.columns
```

```
Index(['Store', 'Date', 'Weekly_Sales', 'Holiday_Flag', 'Temperature',
       'Fuel_Price', 'CPI', 'Unemployment'],
      dtype='object')
```

```
df['Date'] = pd.to_datetime(df['Date'], dayfirst=True,
errors='coerce') #setting "Date" to datetime format

df.set_index('Date', inplace=True)  # Set the date column as the index
df['Weekly_Sales'].plot(figsize=(12,6), title='Weekly Sales Over
Time', xlabel='Date', ylabel='Sales')
plt.show()
```



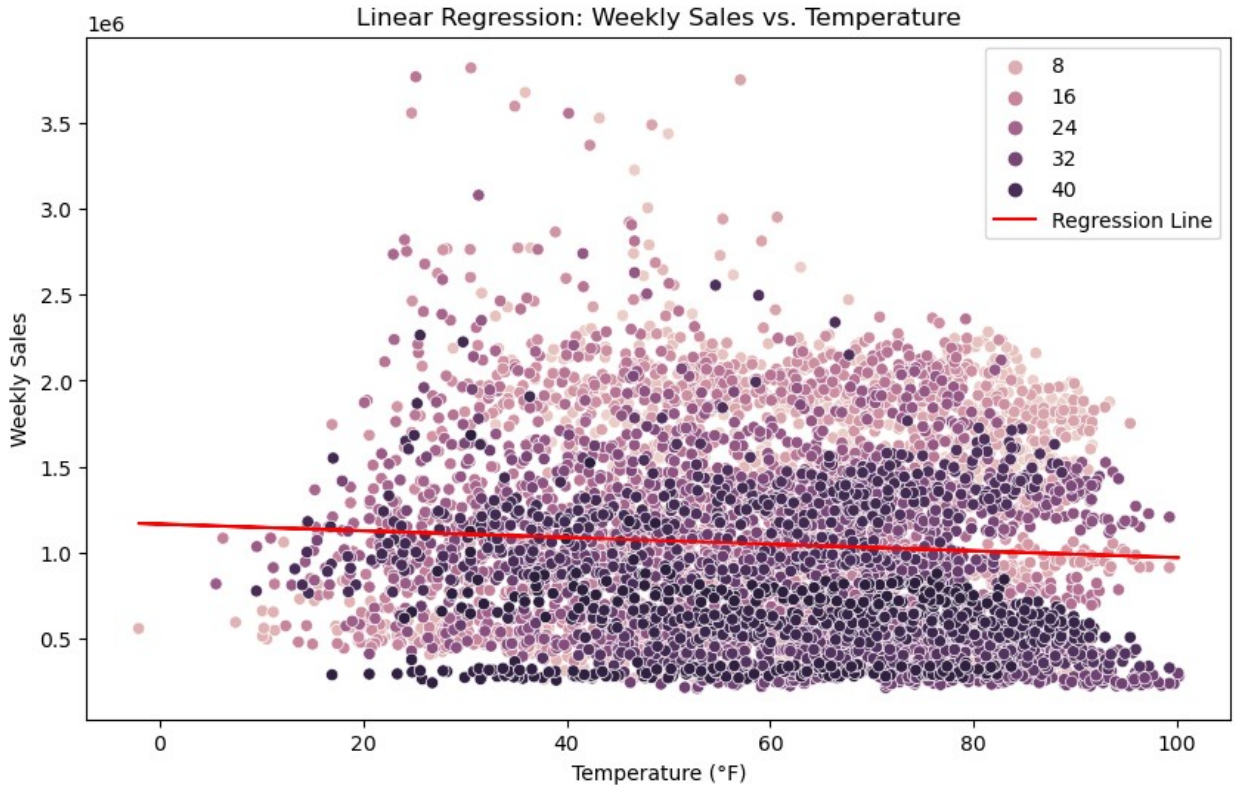
temperature affect the weekly sales

```
correlation = df[['Temperature','Weekly_Sales']].corr()
print(correlation)
```

```
              Temperature  Weekly_Sales
Temperature       1.00000      -0.06381
Weekly_Sales     -0.06381       1.00000
```

```
from sklearn.linear_model import LinearRegression

# Reshape the data
X = df['Temperature'].values.reshape(-1, 1)
y = df['Weekly_Sales'].values

# Create and fit the model
model = LinearRegression()
```

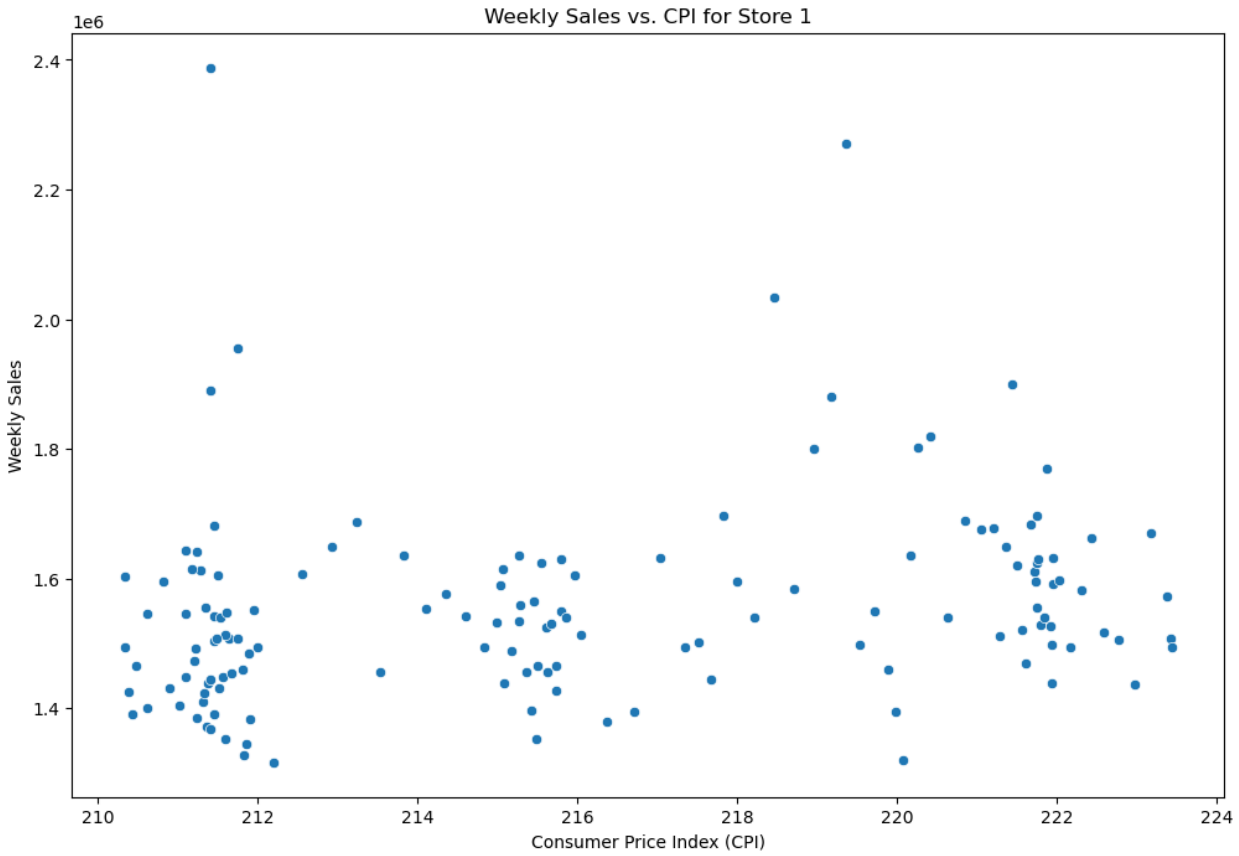
```
model.fit(X, y)

# Plot regression line
plt.figure(figsize=(10,6))
sns.scatterplot(x='Temperature', y='Weekly_Sales', data=df,
hue='Store')
plt.plot(df['Temperature'], model.predict(X), color='red',
label='Regression Line')
plt.title('Linear Regression: Weekly Sales vs. Temperature')
plt.xlabel('Temperature (°F)')
plt.ylabel('Weekly Sales')
plt.legend()
plt.show()

# Get the R-squared value and coefficients
r_squared = model.score(X, y)
print(f"R-squared: {r_squared}")
print(f"Coefficient (slope): {model.coef_[0]}")
print(f"Intercept: {model.intercept_}")
```



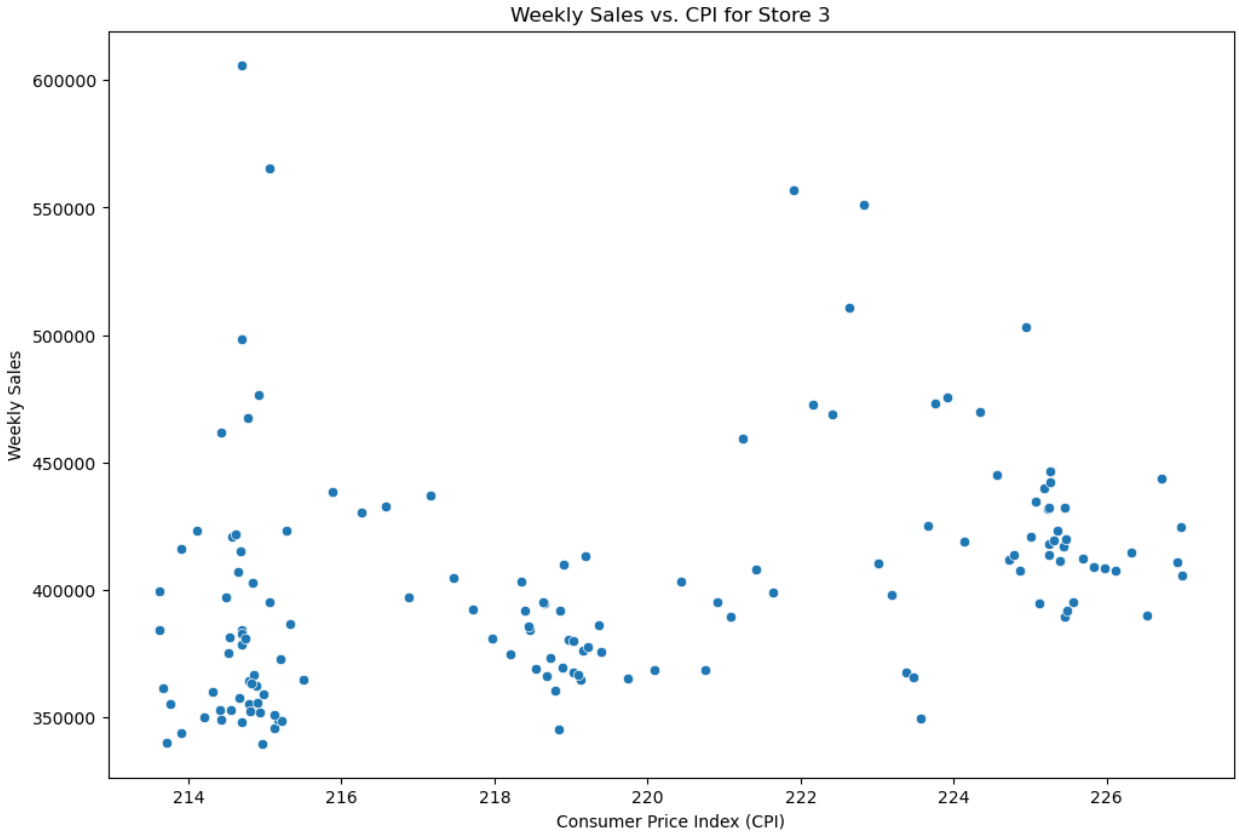

```
R-squared: 0.004071717781964135
Coefficient (slope): -1952.4192272081987
Intercept: 1165406.012792378
```

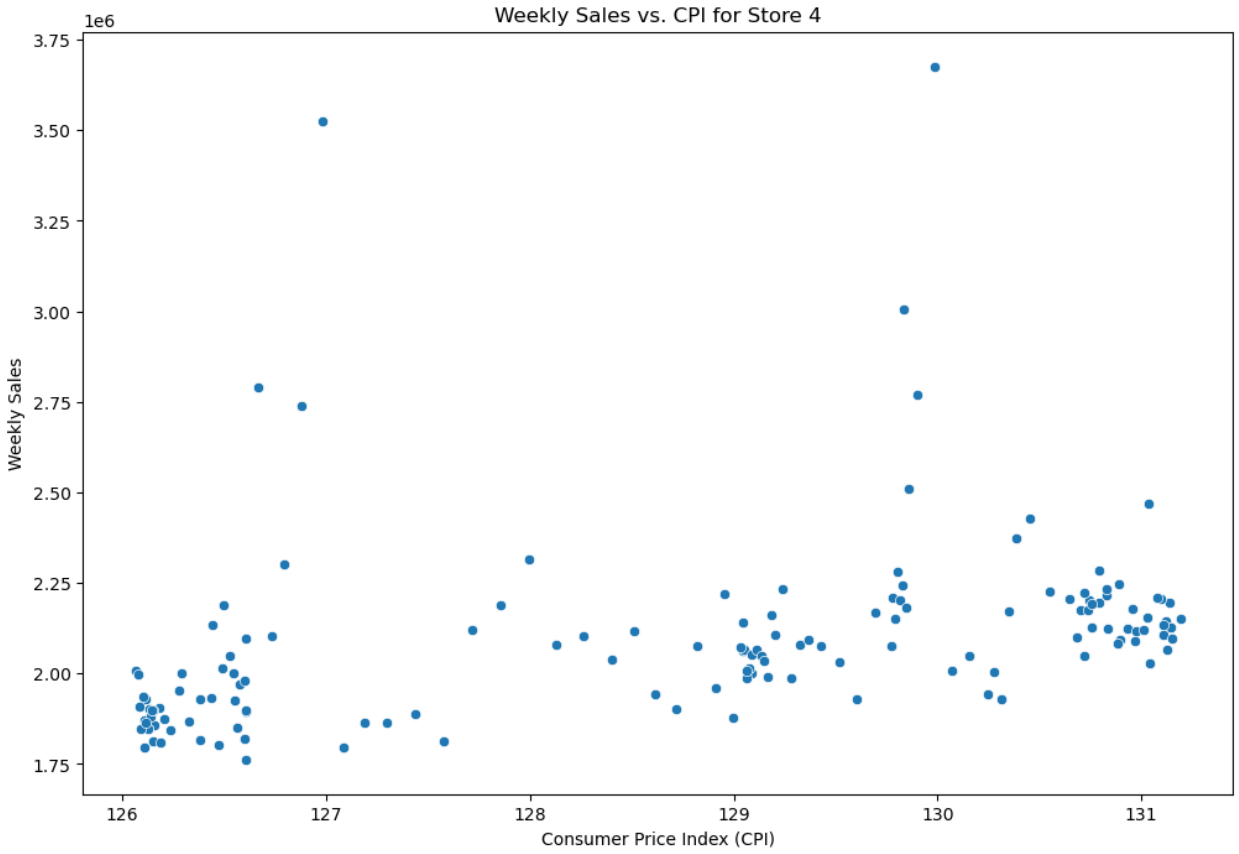
Consumer Price index affecting the weekly sales of various stores

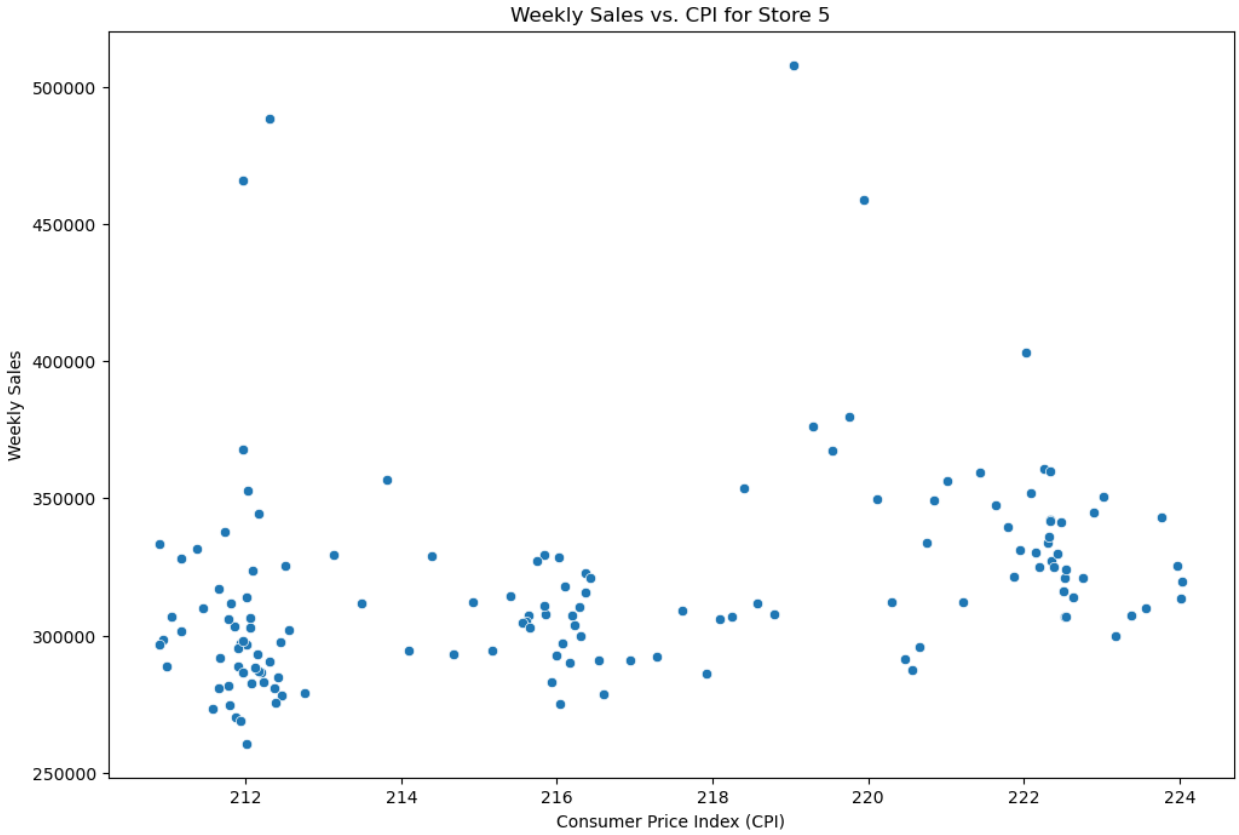
```
for store in df['Store'].unique():
    store_data = df[df['Store'] == store]
    plt.figure(figsize=(12,8))
    sns.scatterplot(data=store_data, x='CPI', y='Weekly_Sales')
    plt.title(f'Weekly Sales vs. CPI for Store {store}')
    plt.xlabel('Consumer Price Index (CPI)')
    plt.ylabel('Weekly Sales')
    plt.show()
```

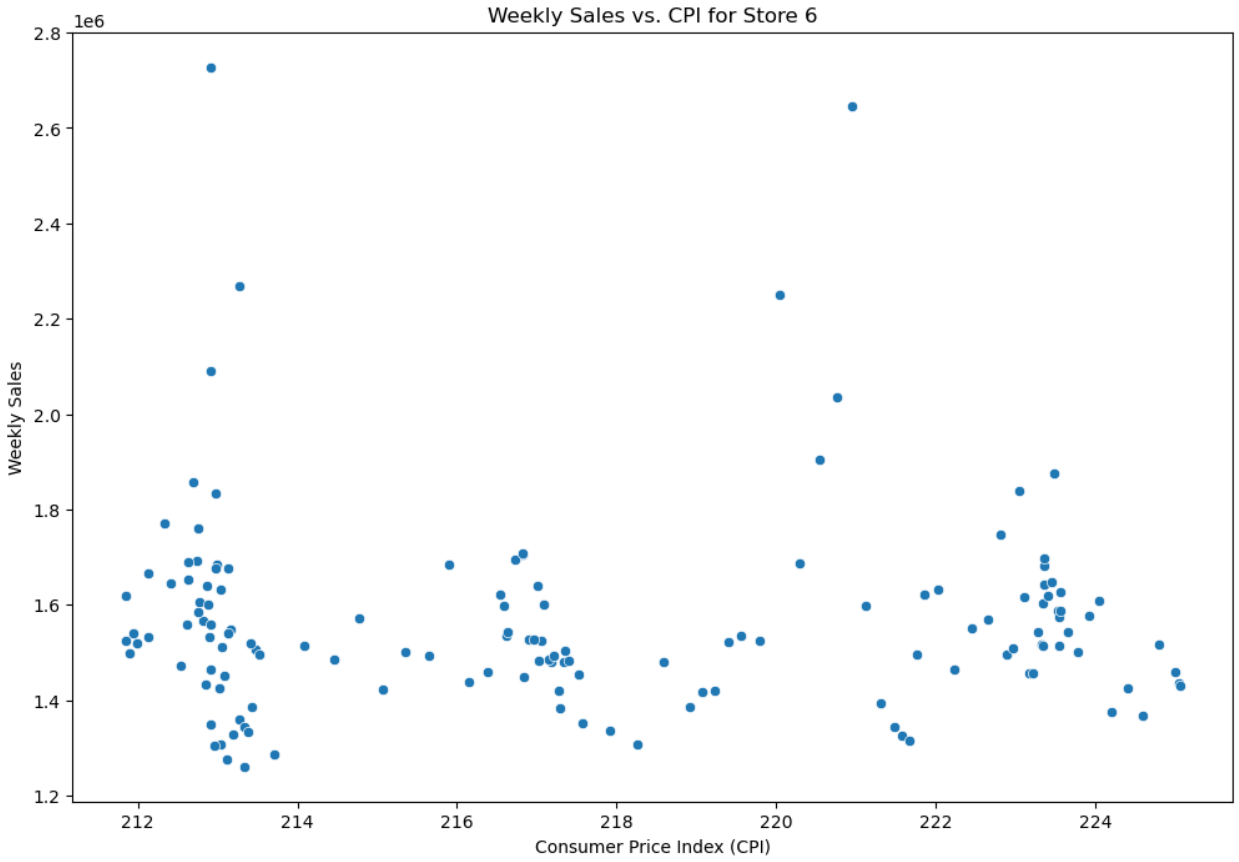


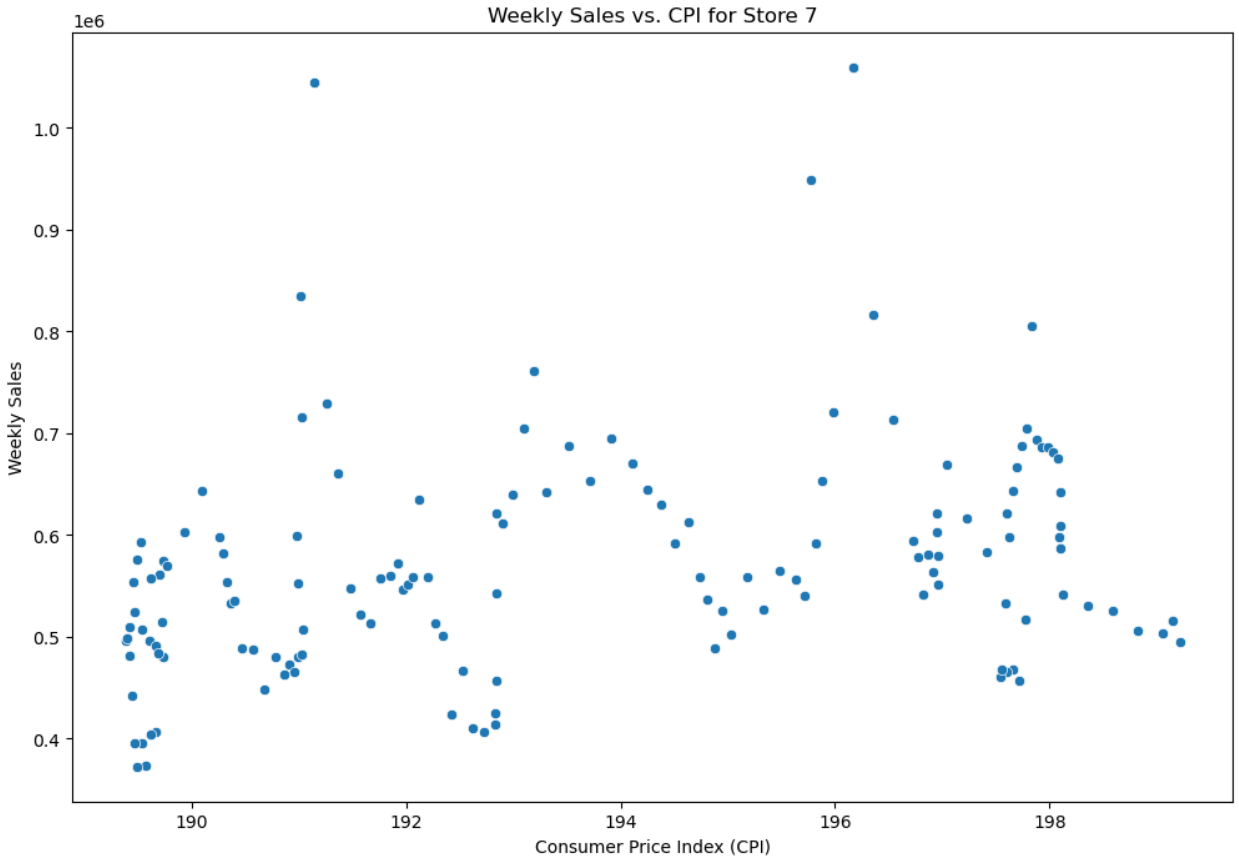

Weekly Sales vs. CPI for Store 2
1e6
3.50
3.25
3.00
2.75
2.50
2.25
2.00
1.75
Weekly Sales
210
212
214
216
218
220
222
Consumer Price Index (CPI)

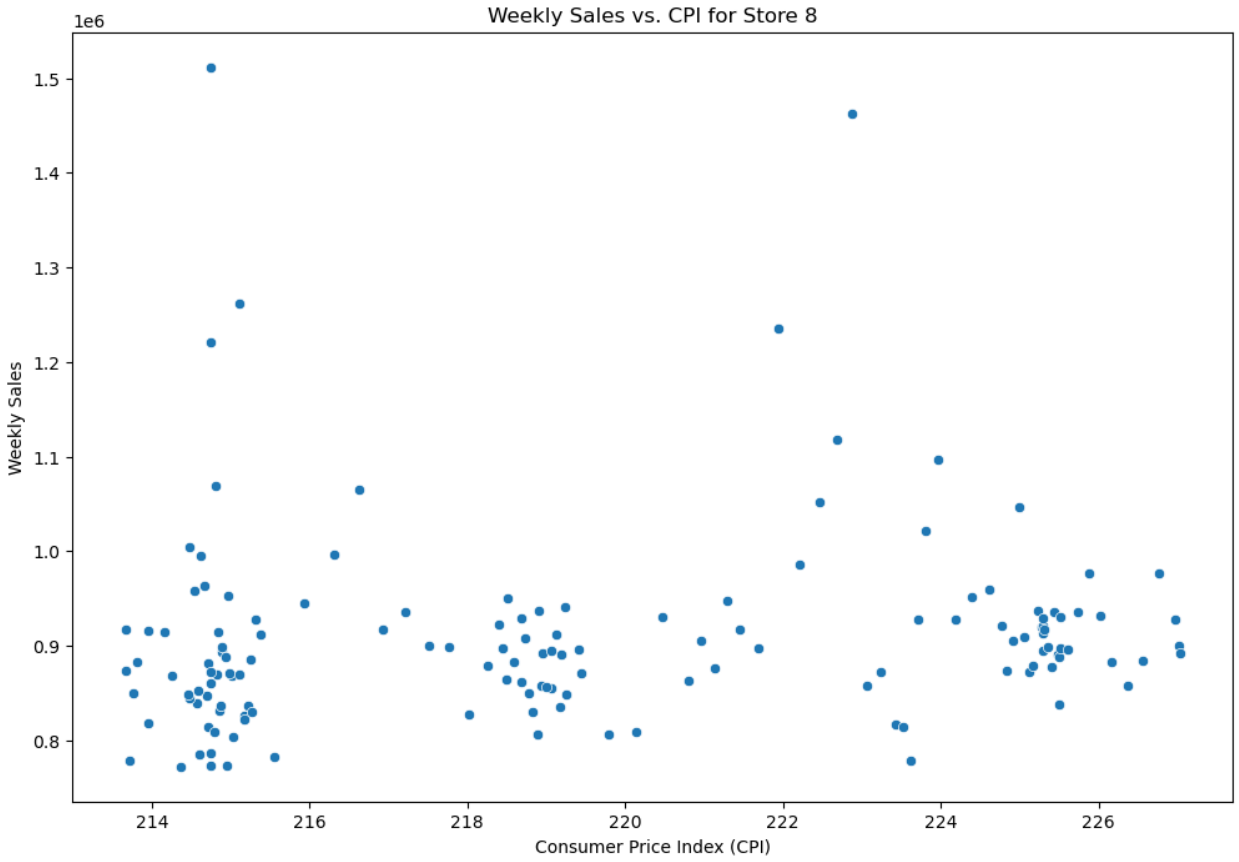

Weekly Sales vs. CPI for Store 3
Weekly Sales
600000
550000
500000
450000
400000
350000
214
216
218
220
222
224
226
Consumer Price Index (CPI)

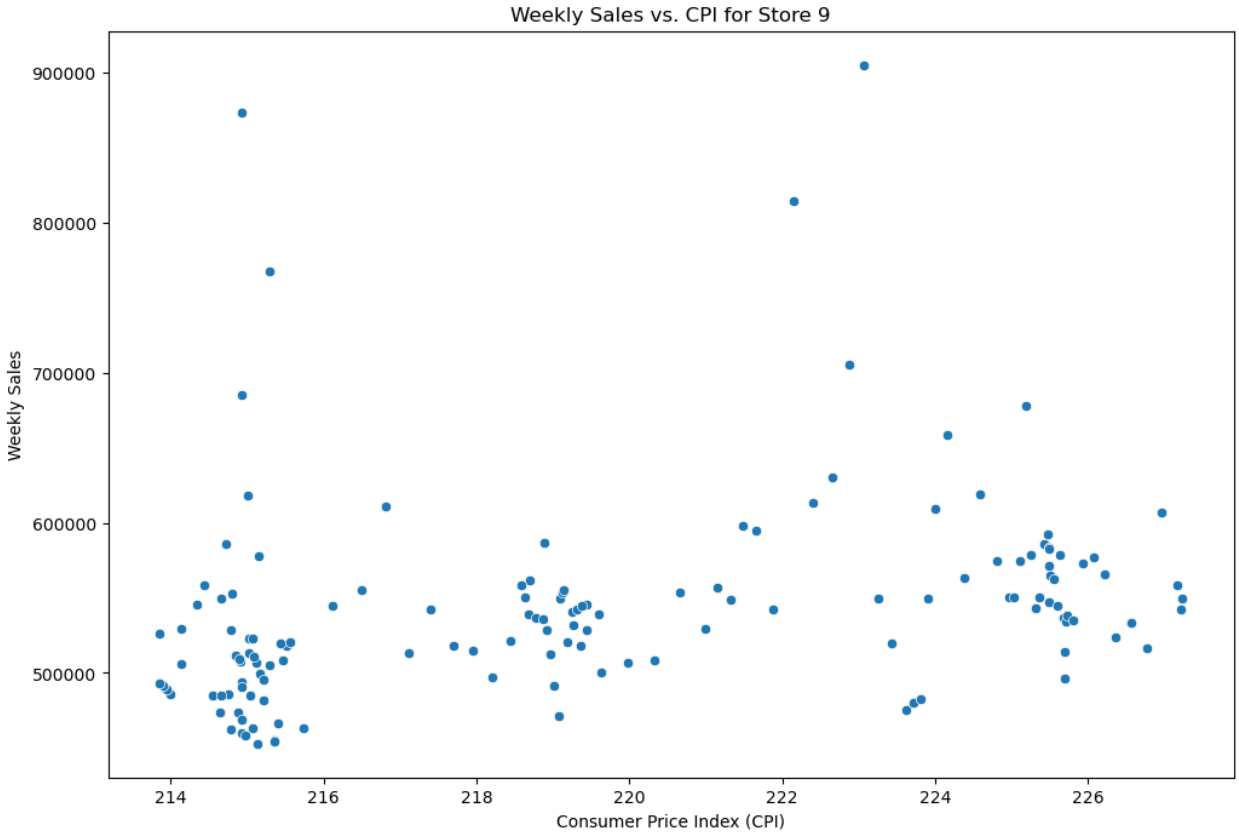

Weekly Sales vs. CPI for Store 4
1e6
3.75
3.50
3.25
3.00
2.75
2.50
2.25
2.00
1.75
Weekly Sales
126
127
128
129
130
131
Consumer Price Index (CPI)

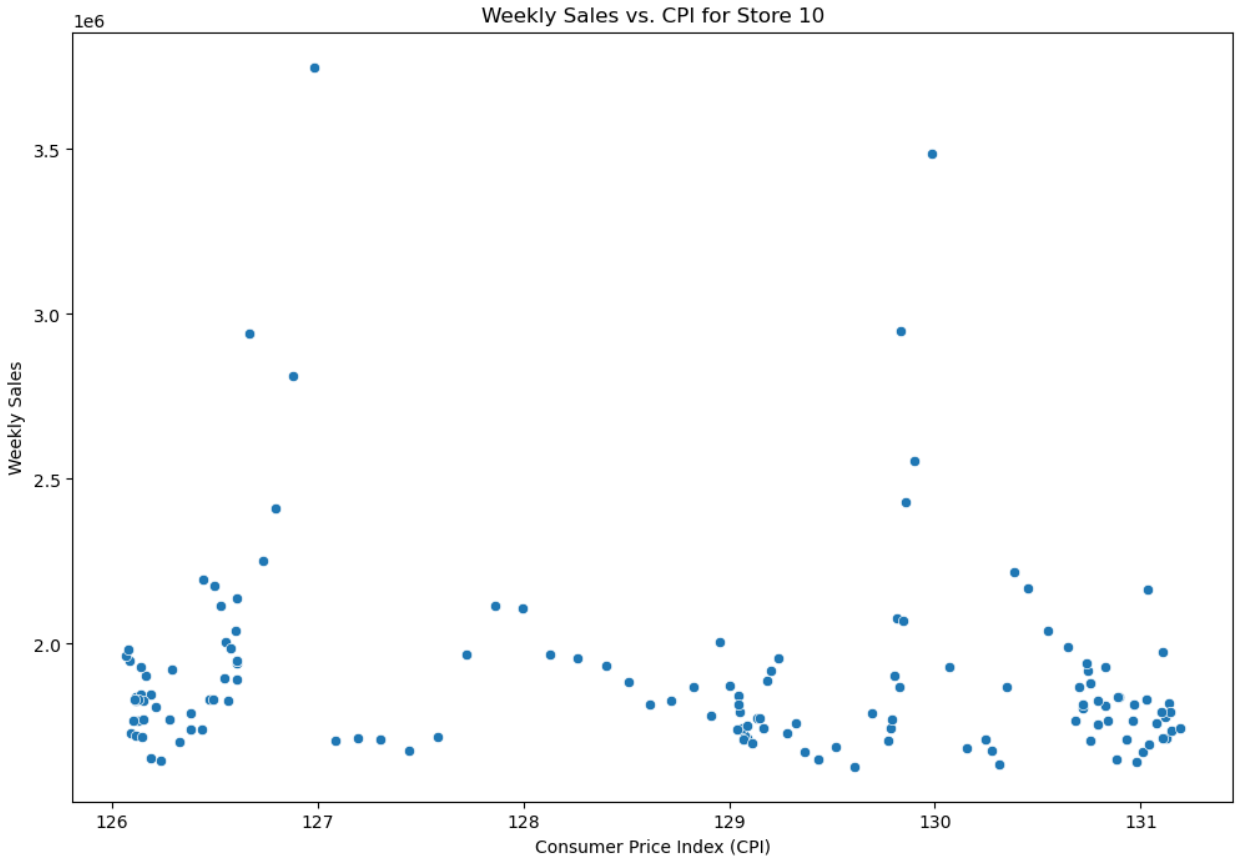

Weekly Sales vs. CPI for Store 5
Weekly Sales
500000
450000
400000
350000
300000
250000
212
214
216
218
220
222
224
Consumer Price Index (CPI)

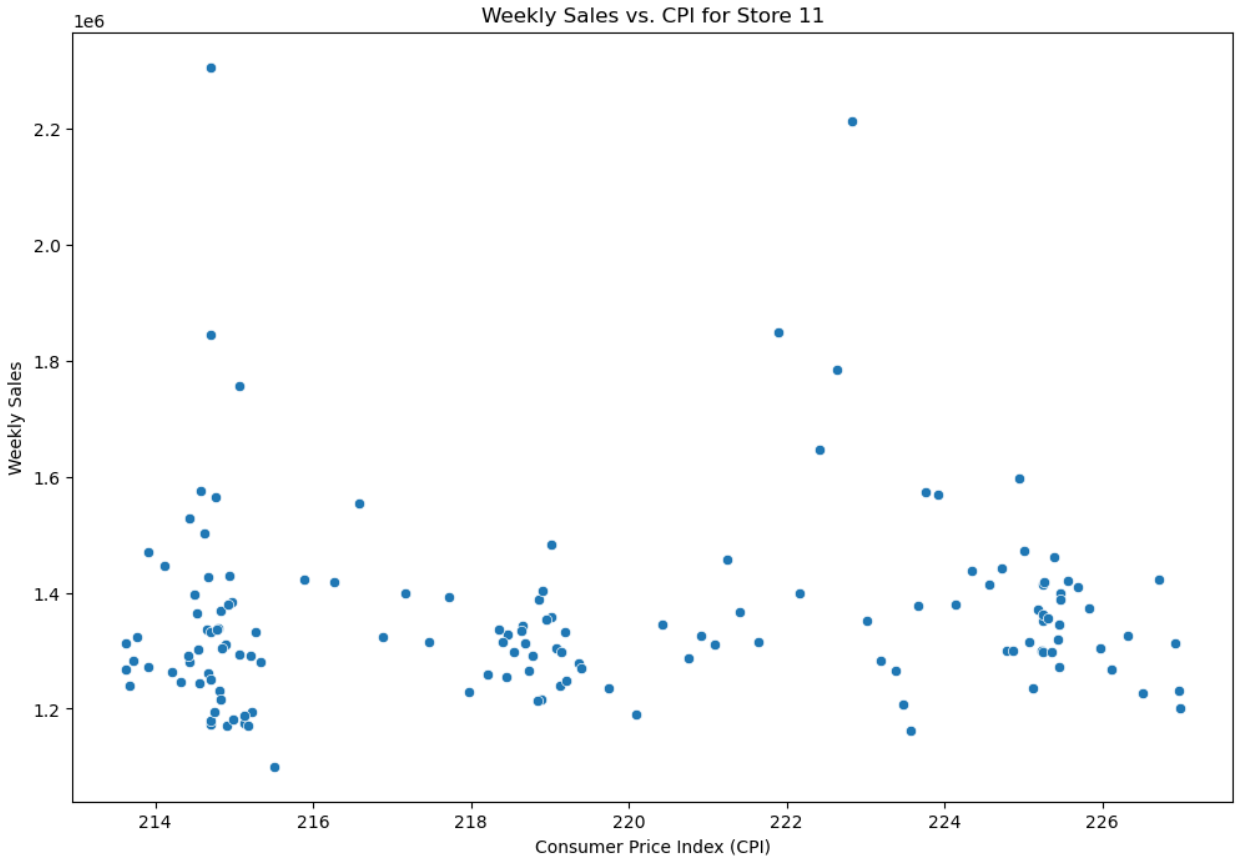

Weekly Sales vs. CPI for Store 6
1e6
2.8
2.6
2.4
2.2
2.0
1.8
1.6
1.4
1.2
Weekly Sales
212
214
216
218
220
222
224
Consumer Price Index (CPI)

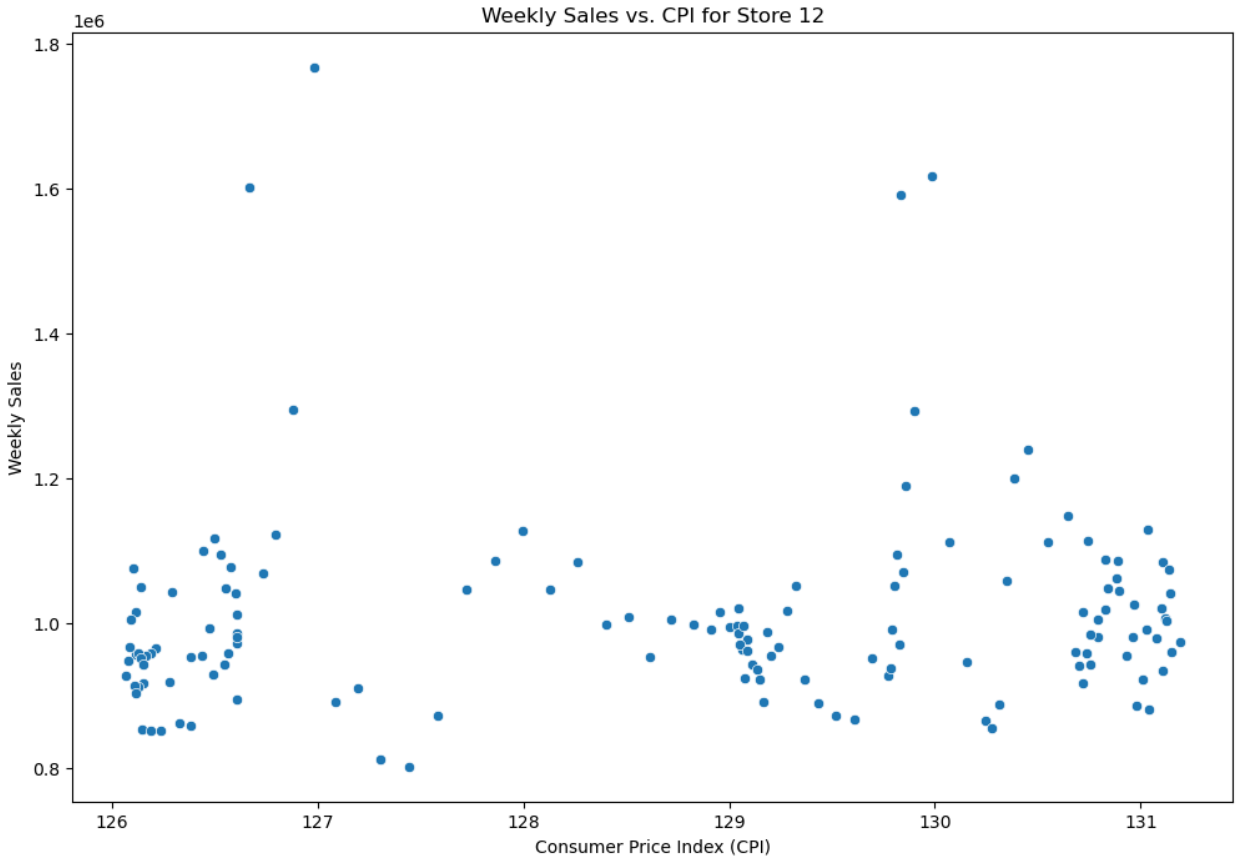

Weekly Sales vs. CPI for Store 7
1e6
1.0
0.9
0.8
0.7
0.6
0.5
0.4
Weekly Sales
190
192
194
196
198
Consumer Price Index (CPI)

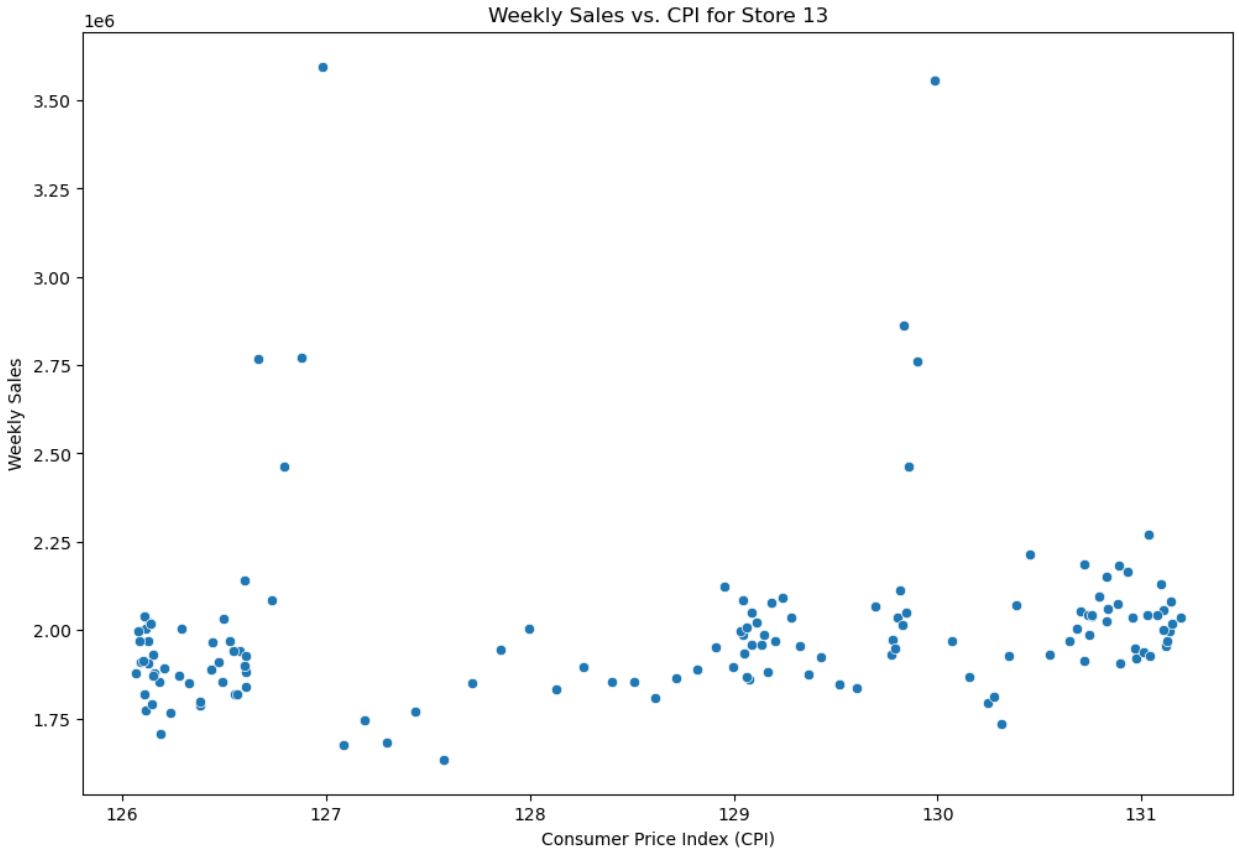

Weekly Sales vs. CPI for Store 8
1e6
1.5
1.4
1.3
1.2
1.1
1.0
0.9
0.8
Weekly Sales
214
216
218
220
222
224
226
Consumer Price Index (CPI)

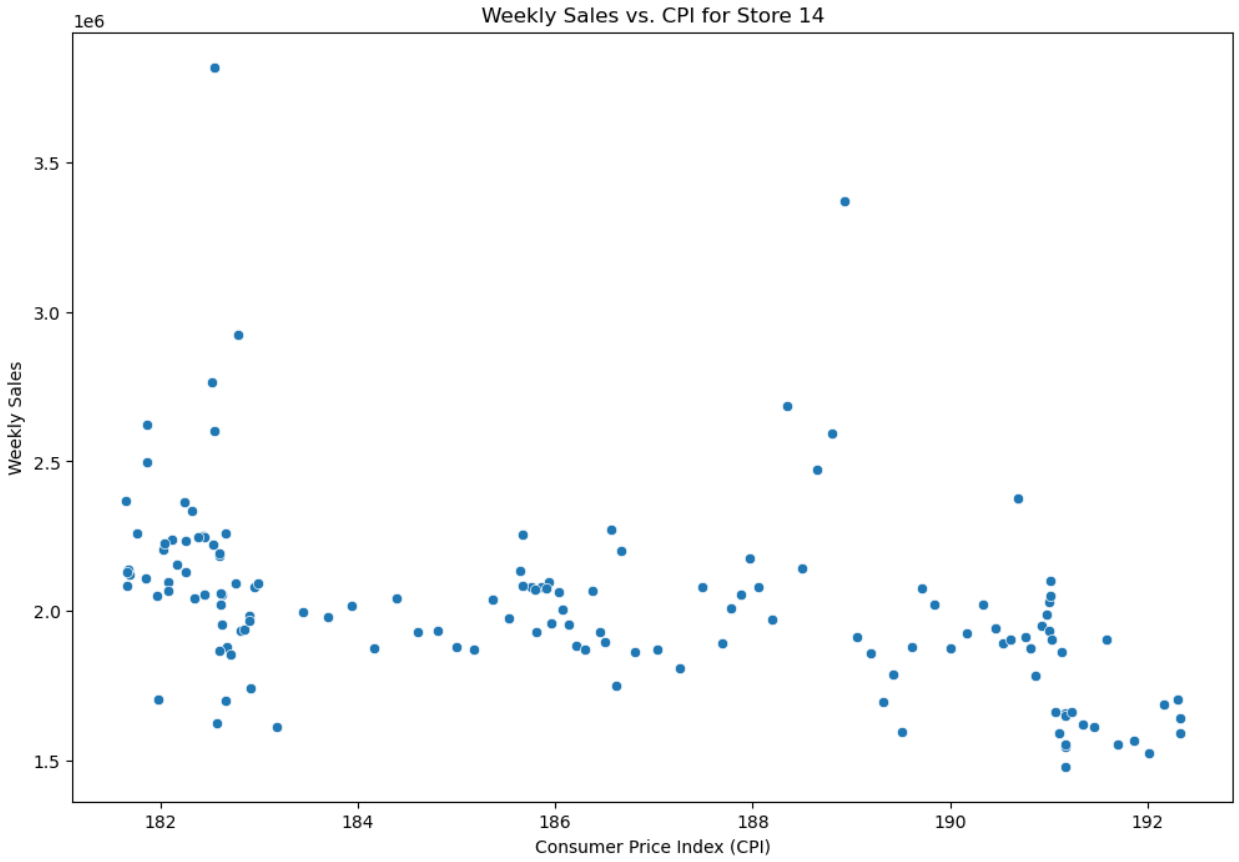

Weekly Sales vs. CPI for Store 9
900000
800000
700000
600000
500000
Weekly Sales
214
216
218
220
222
224
226
Consumer Price Index (CPI)

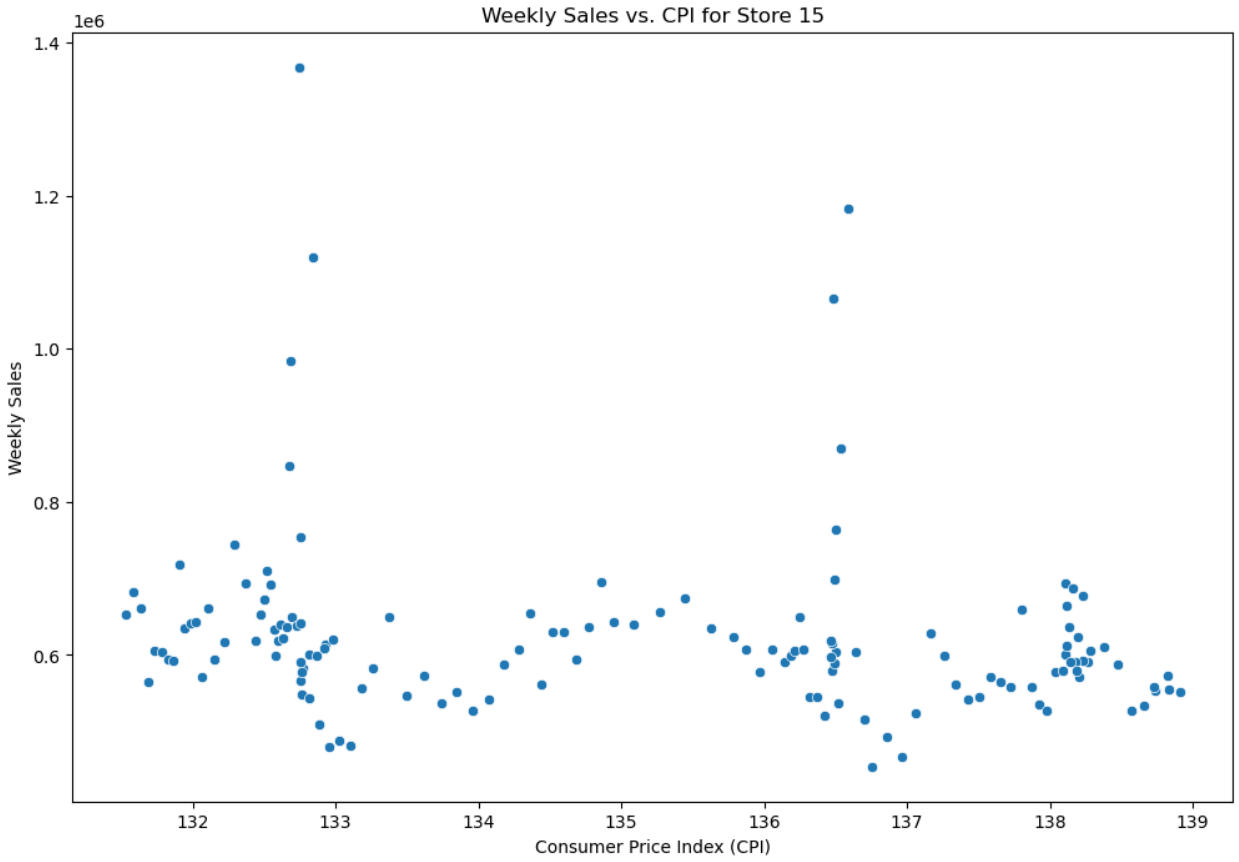

Weekly Sales vs. CPI for Store 10
1e6
3.5
3.0
2.5
2.0
Weekly Sales
126
127
128
129
130
131
Consumer Price Index (CPI)

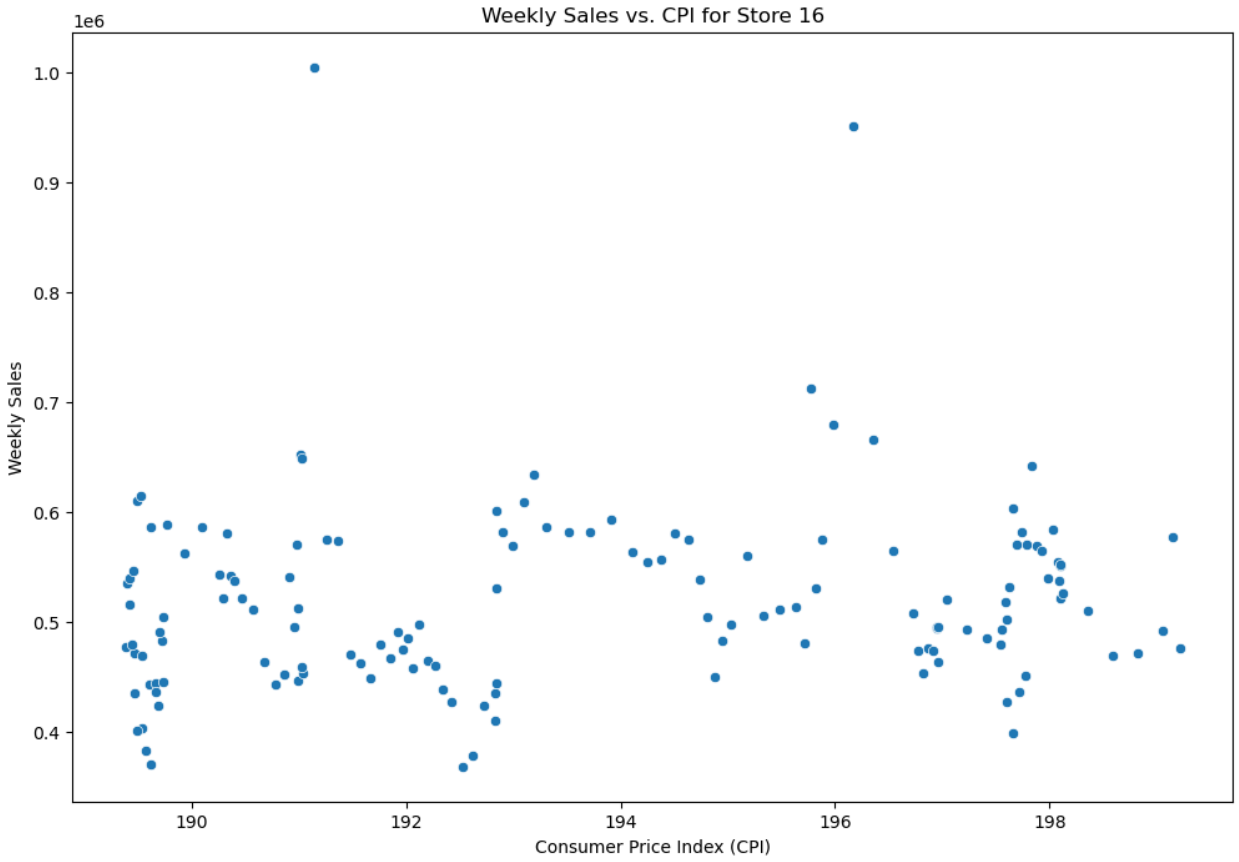

Weekly Sales vs. CPI for Store 11
1e6
2.2
2.0
1.8
1.6
1.4
1.2
Weekly Sales
214
216
218
220
222
224
226
Consumer Price Index (CPI)

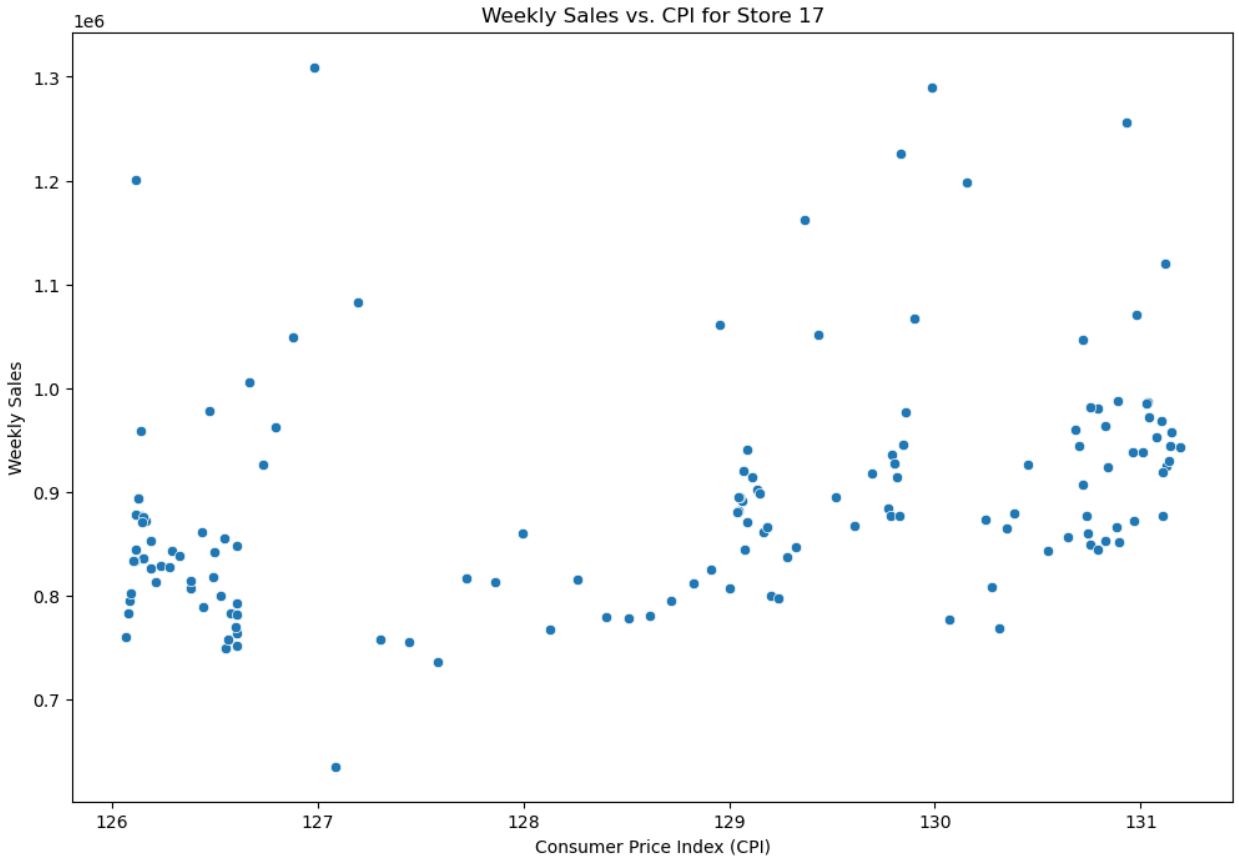

Weekly Sales vs. CPI for Store 12
1e6
1.8
1.6
1.4
1.2
1.0
0.8
Weekly Sales
126
127
128
129
130
131
Consumer Price Index (CPI)

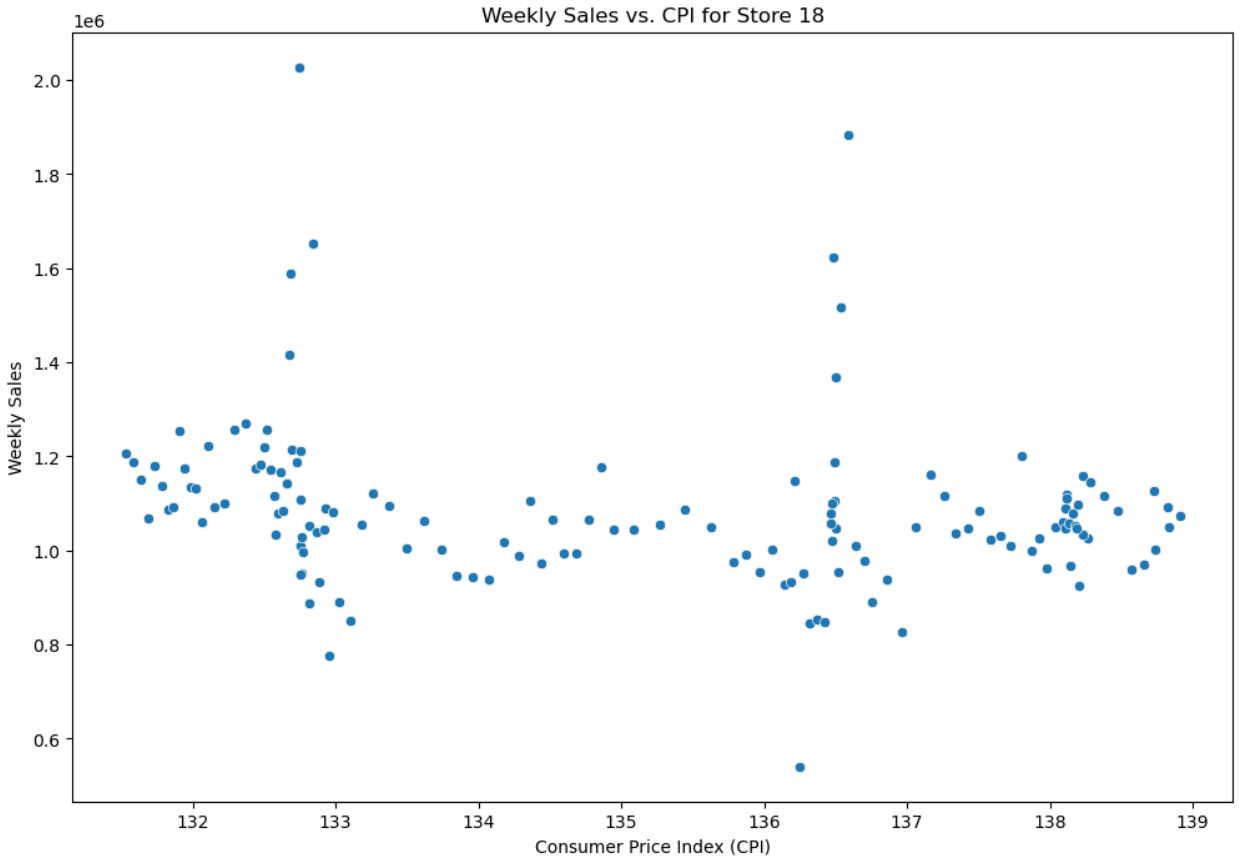

Weekly Sales vs. CPI for Store 13
1e6
3.50
3.25
3.00
2.75
2.50
2.25
2.00
1.75
Weekly Sales
126
127
128
129
130
131
Consumer Price Index (CPI)

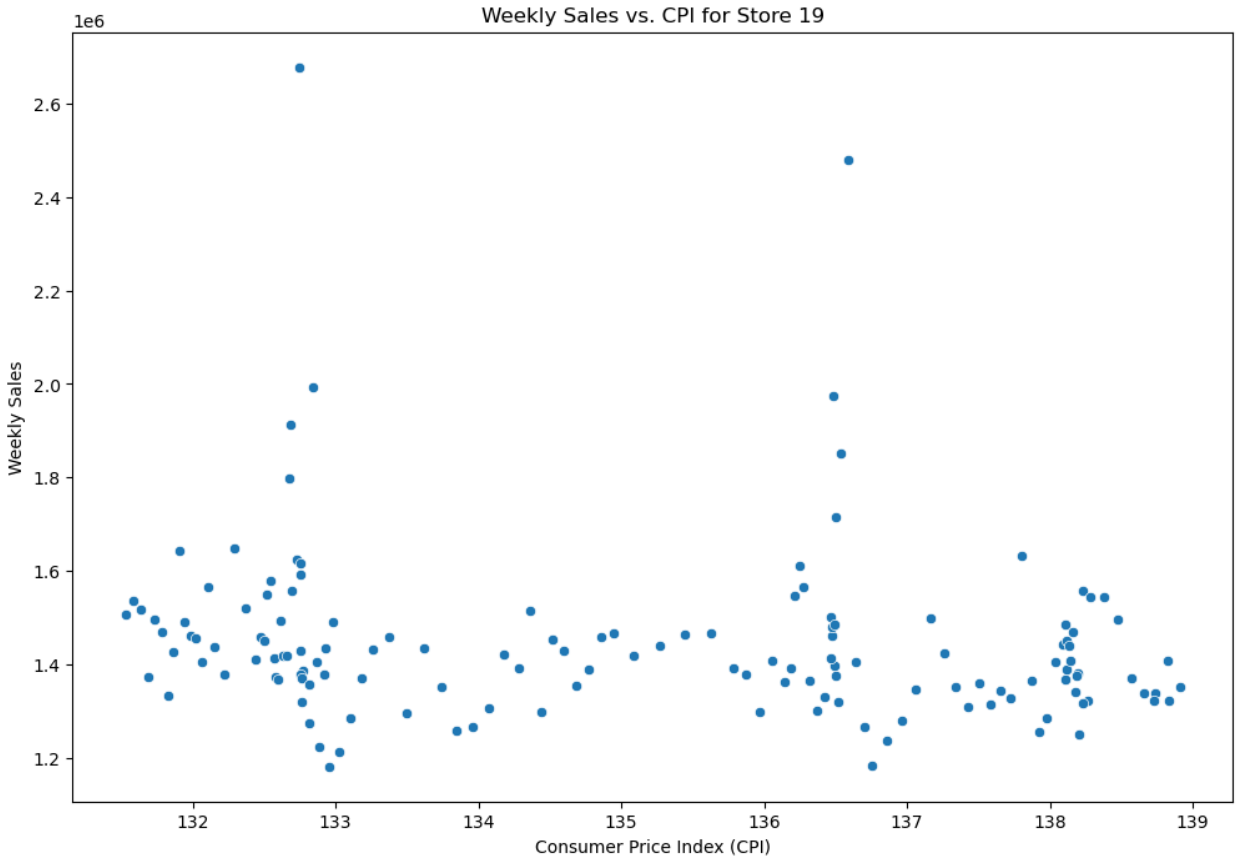

Weekly Sales vs. CPI for Store 14
1e6
3.5
3.0
2.5
2.0
1.5
Weekly Sales
182
184
186
188
190
192
Consumer Price Index (CPI)

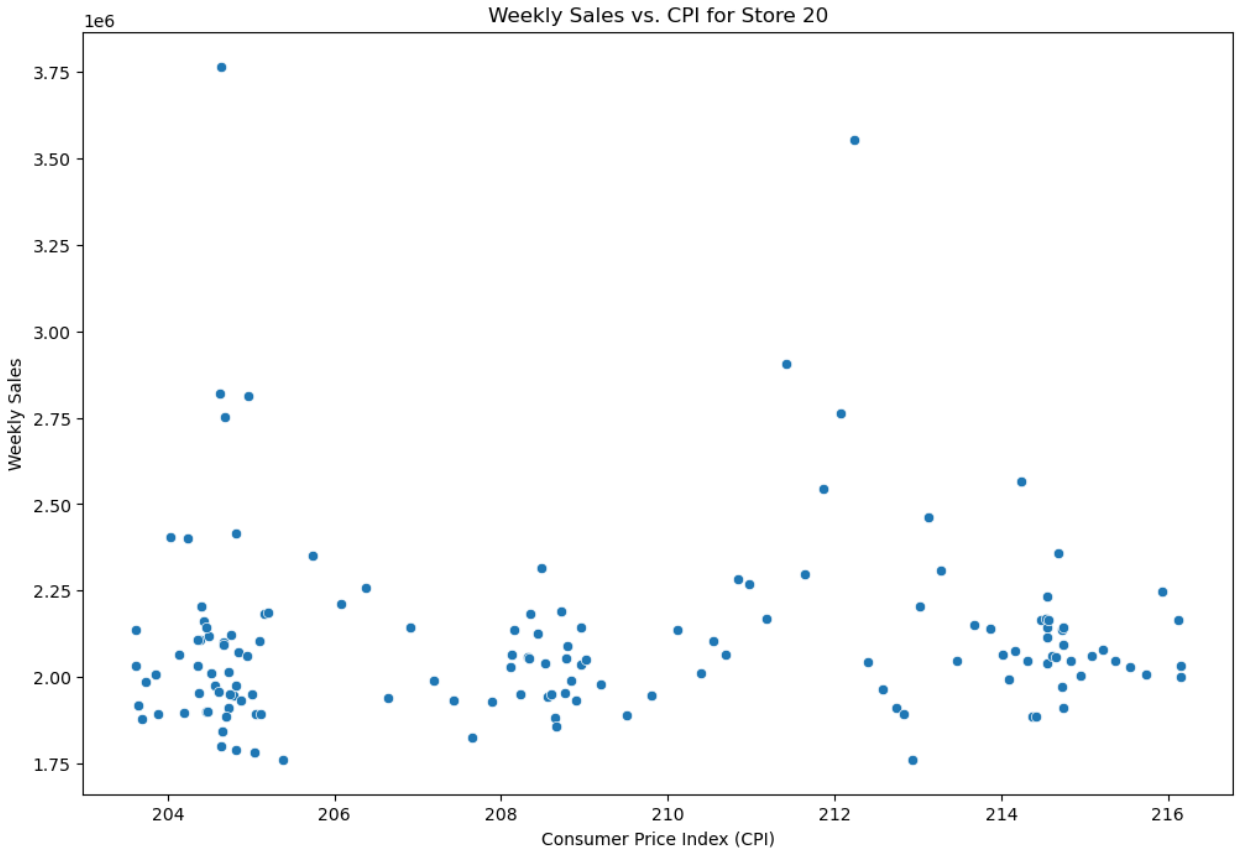

Weekly Sales vs. CPI for Store 15
1e6
1.4
1.2
1.0
0.8
0.6
Weekly Sales
132
133
134
135
136
137
138
139
Consumer Price Index (CPI)

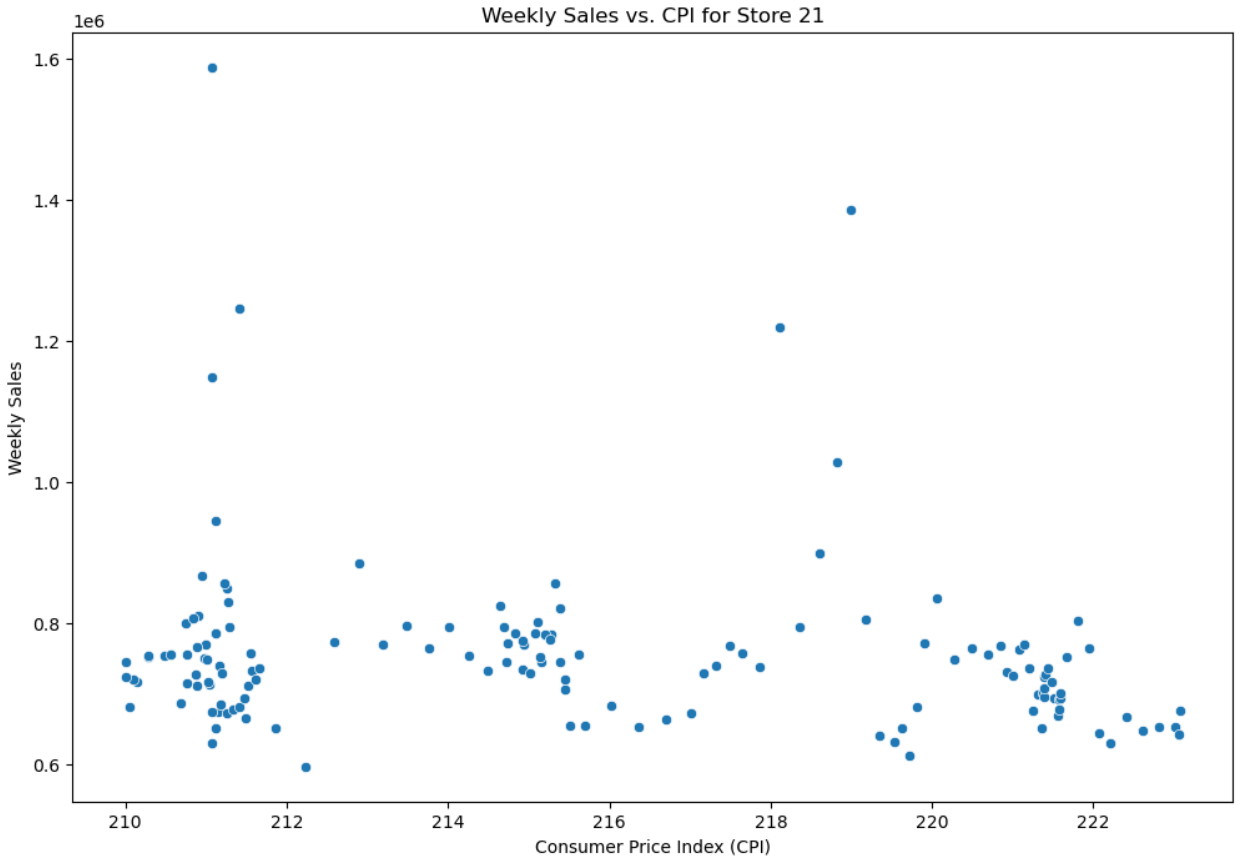

Weekly Sales vs. CPI for Store 16
1e6
1.0
0.9
0.8
0.7
0.6
0.5
0.4
Weekly Sales
190
192
194
196
198
Consumer Price Index (CPI)

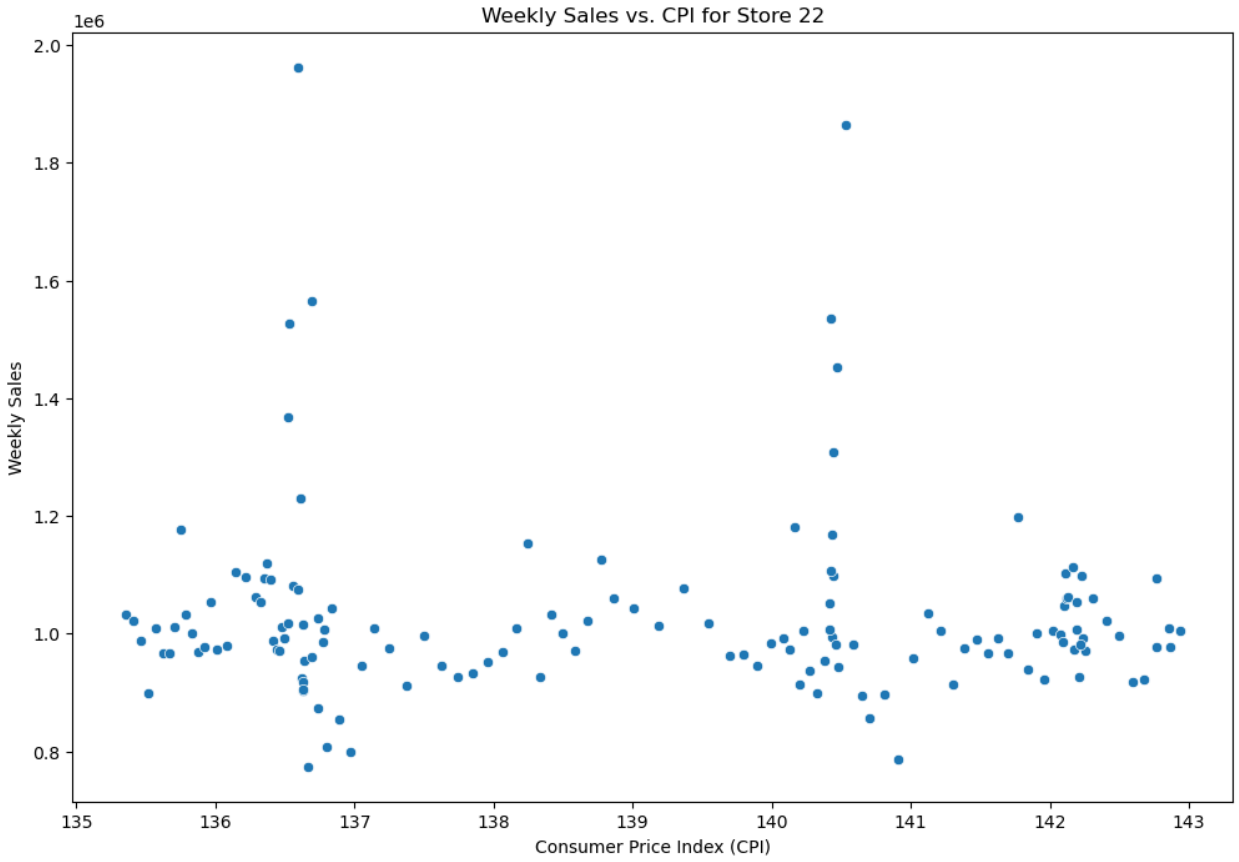

Weekly Sales vs. CPI for Store 17
1e6
1.3
1.2
1.1
1.0
0.9
0.8
0.7
Weekly Sales
126
127
128
129
130
131
Consumer Price Index (CPI)

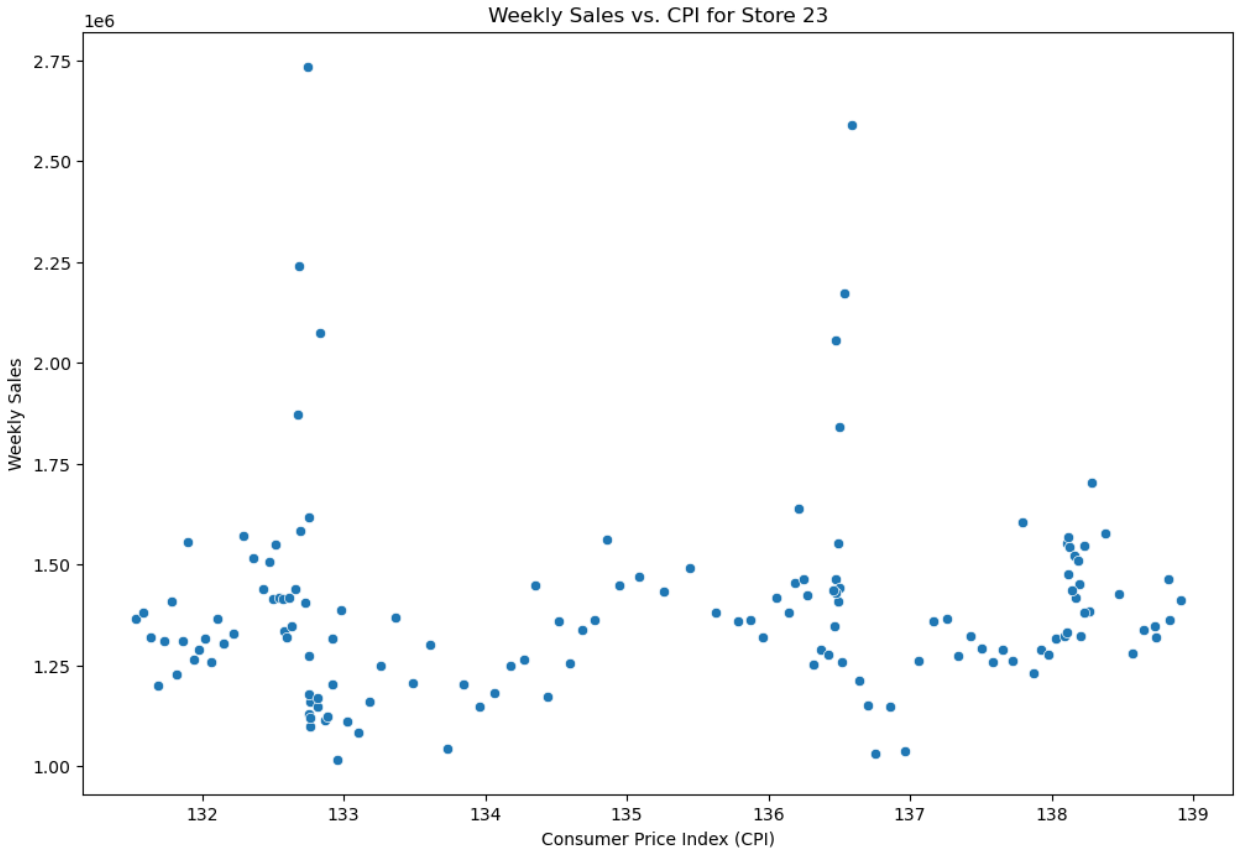

Weekly Sales vs. CPI for Store 18
1e6
2.0
1.8
1.6
1.4
1.2
1.0
0.8
0.6
Weekly Sales
132
133
134
135
136
137
138
139
Consumer Price Index (CPI)

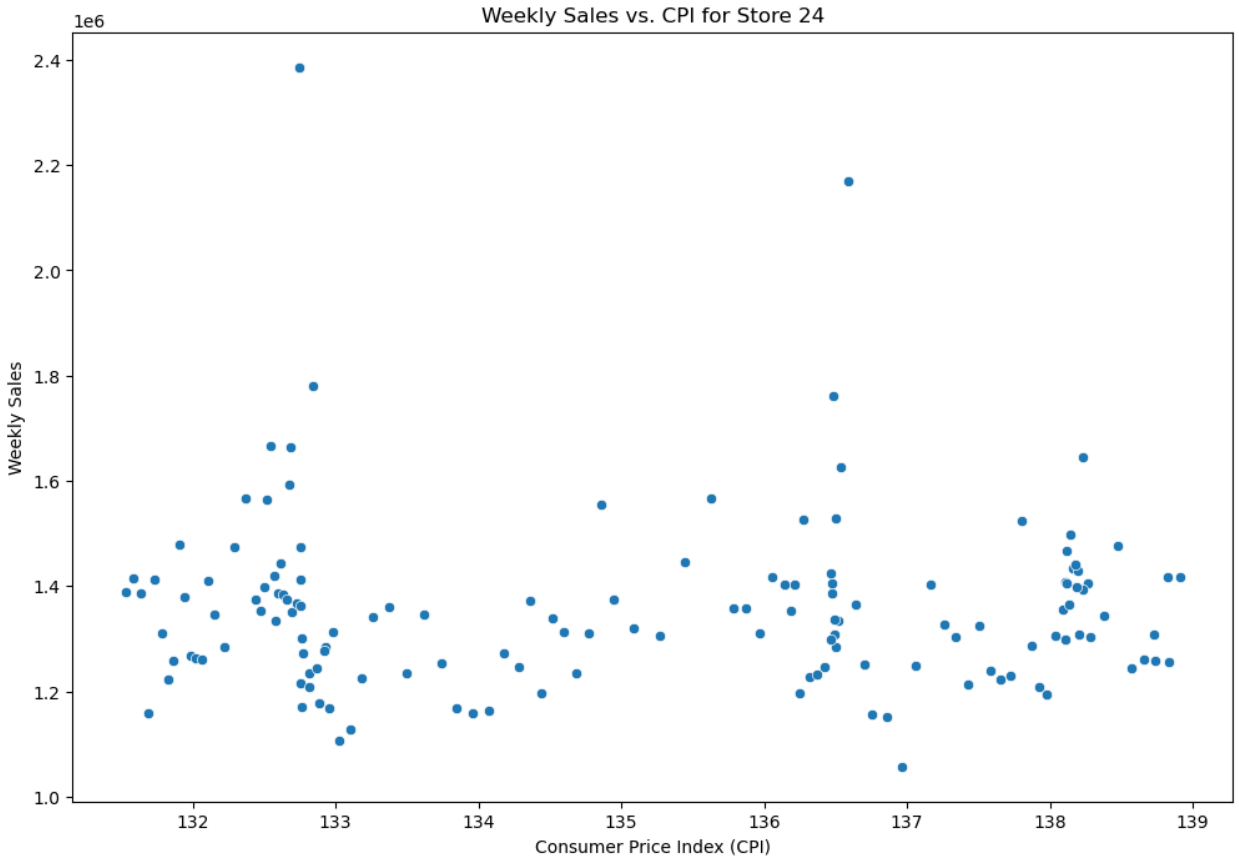

Weekly Sales vs. CPI for Store 19
1e6
2.6
2.4
2.2
2.0
1.8
1.6
1.4
1.2
Weekly Sales
132
133
134
135
136
137
138
139
Consumer Price Index (CPI)

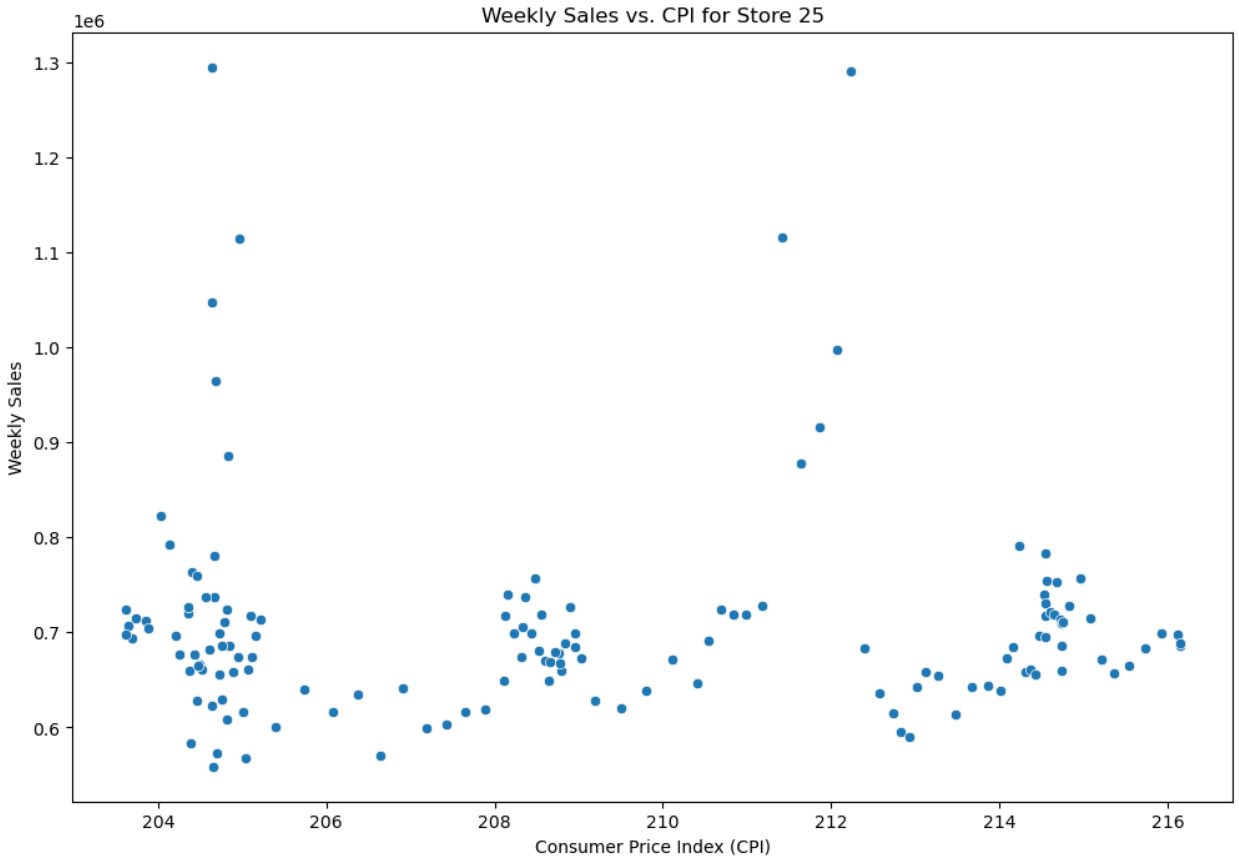

Weekly Sales vs. CPI for Store 20
1e6
3.75
3.50
3.25
3.00
2.75
2.50
2.25
2.00
1.75
Weekly Sales
204
206
208
210
212
214
216
Consumer Price Index (CPI)

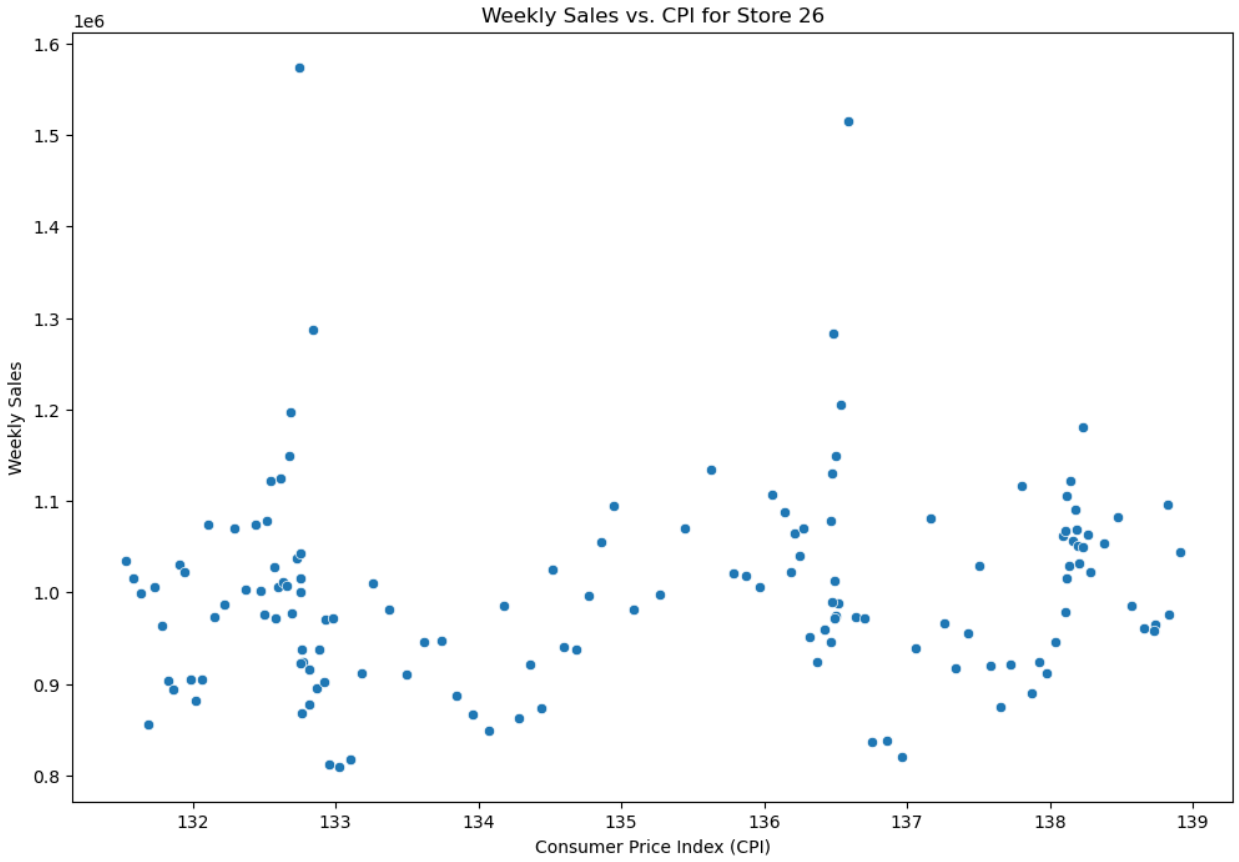

Weekly Sales vs. CPI for Store 21
1e6
1.6
1.4
1.2
1.0
0.8
0.6
Weekly Sales
210
212
214
216
218
220
222
Consumer Price Index (CPI)

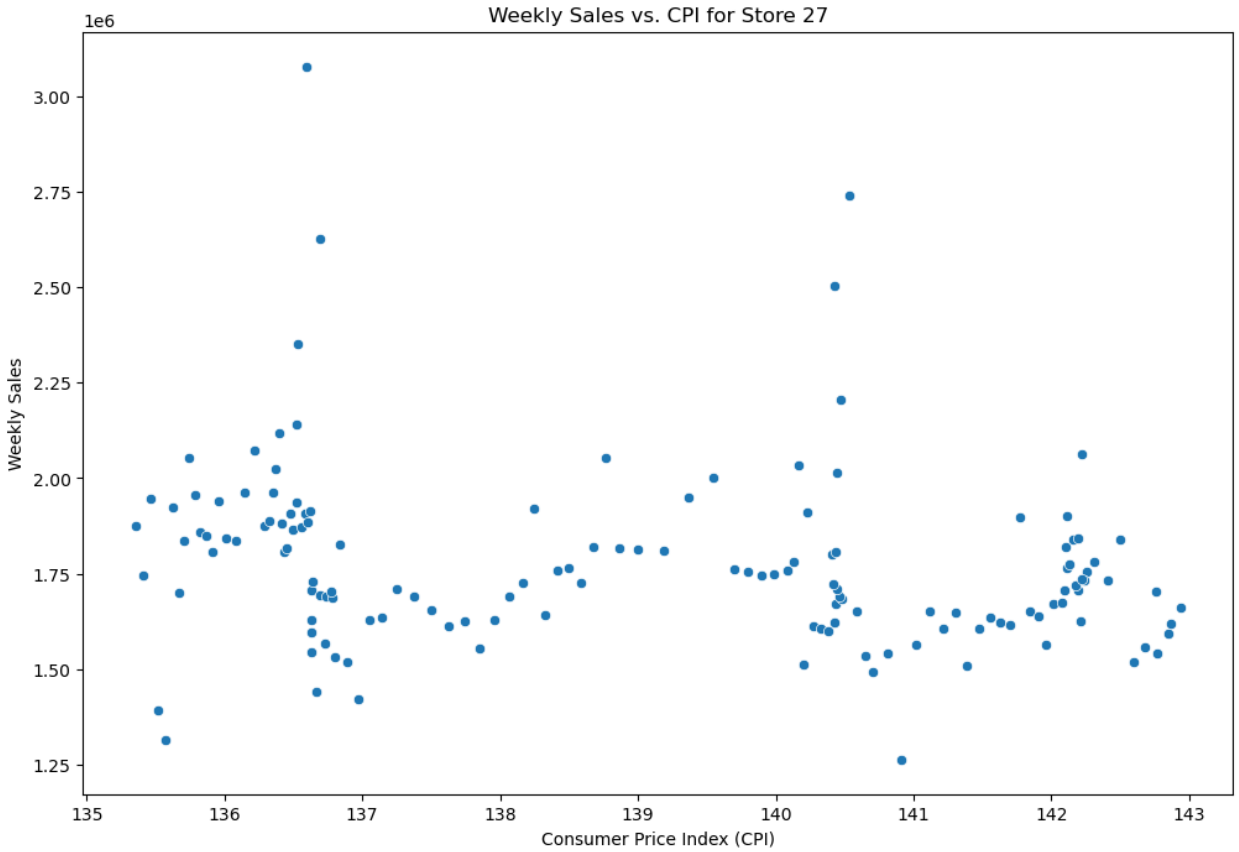

Weekly Sales vs. CPI for Store 22
1e6
2.0
1.8
1.6
1.4
1.2
1.0
0.8
Weekly Sales
135
136
137
138
139
140
141
142
143
Consumer Price Index (CPI)

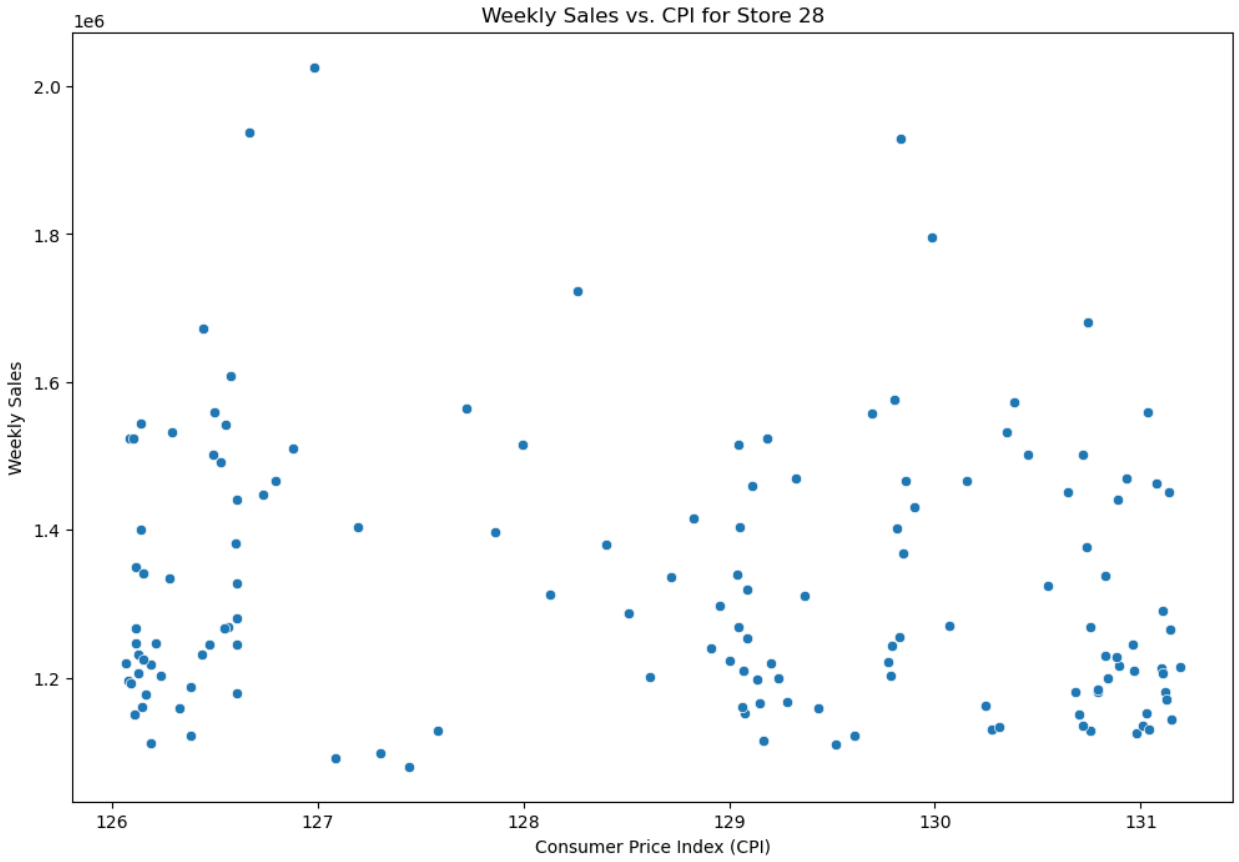

Weekly Sales vs. CPI for Store 23
1e6
2.75
2.50
2.25
2.00
1.75
1.50
1.25
1.00
Weekly Sales
132
133
134
135
136
137
138
139
Consumer Price Index (CPI)

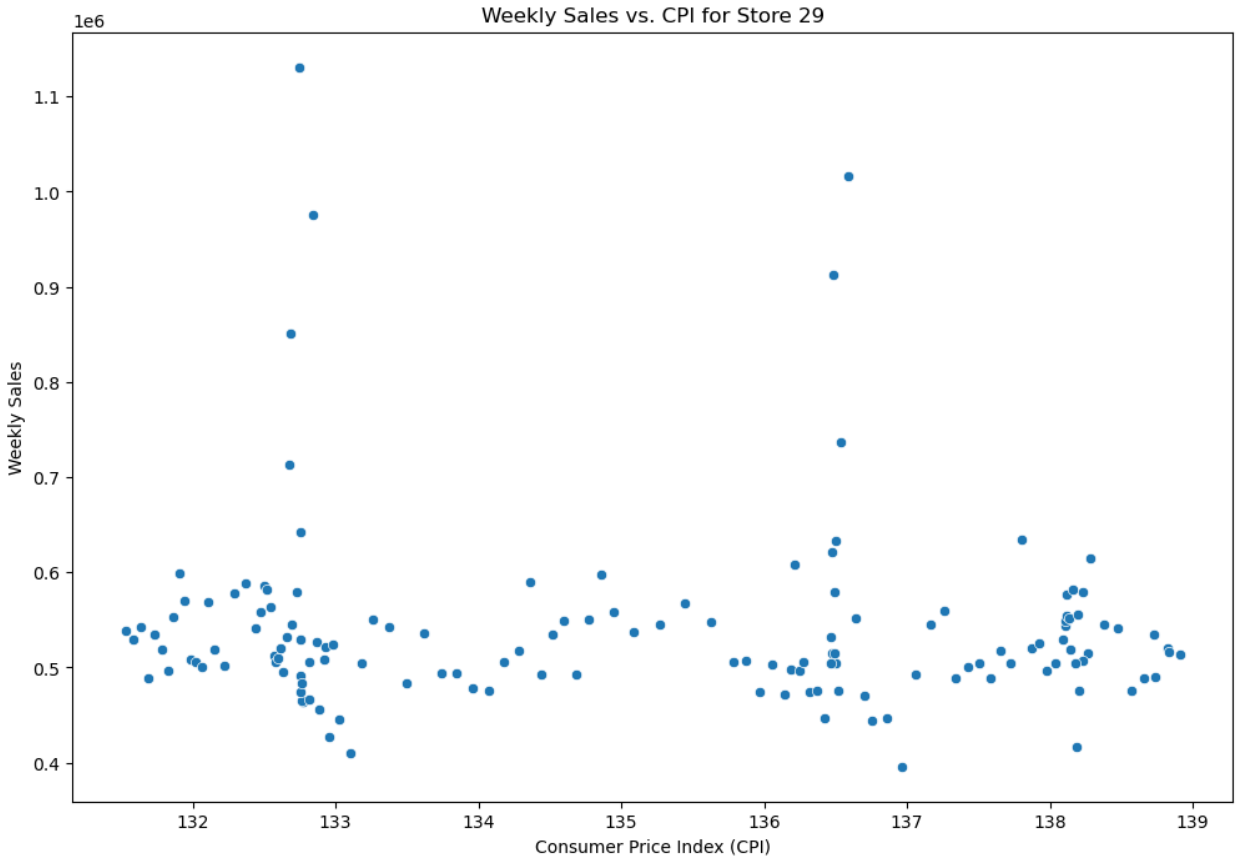

Weekly Sales vs. CPI for Store 24
1e6
2.4
2.2
2.0
1.8
1.6
1.4
1.2
1.0
Weekly Sales
132
133
134
135
136
137
138
139
Consumer Price Index (CPI)

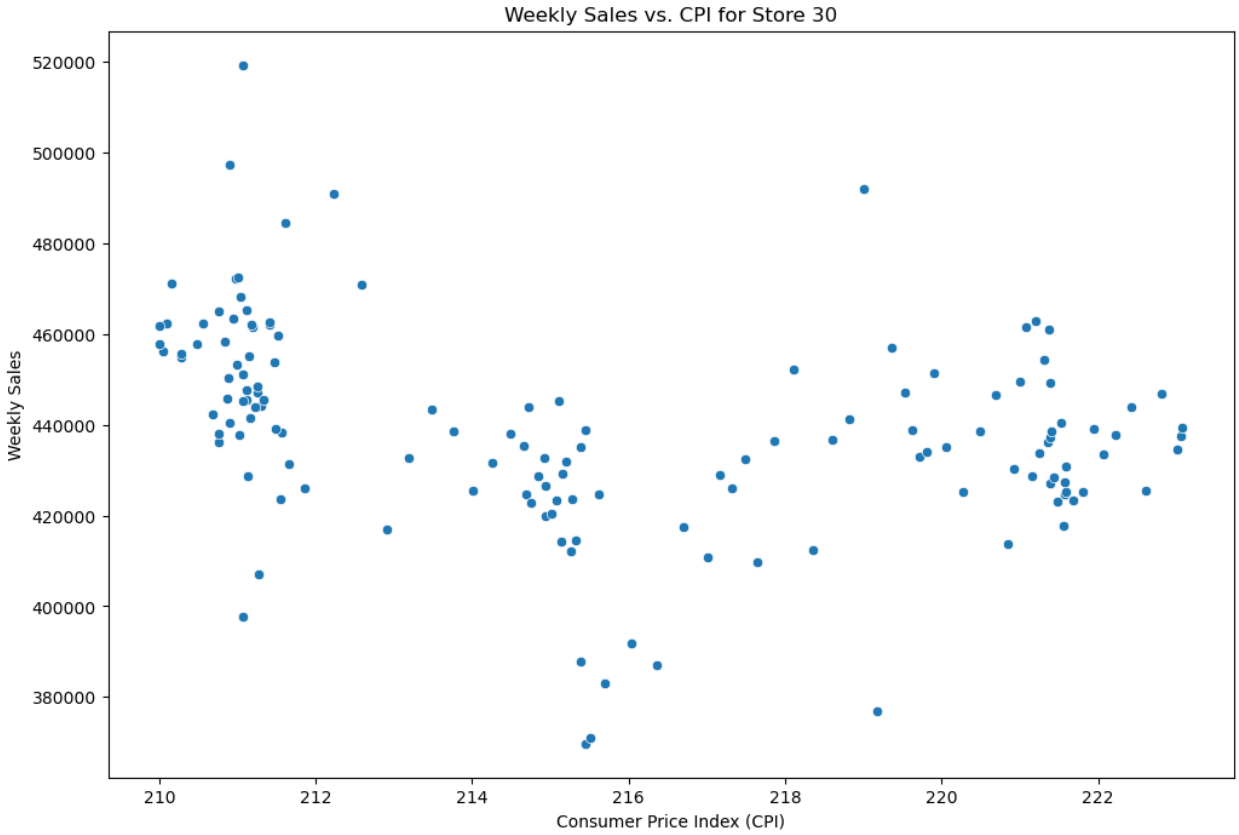

Weekly Sales vs. CPI for Store 25
1e6
1.3
1.2
1.1
1.0
0.9
0.8
0.7
0.6
Weekly Sales
204
206
208
210
212
214
216
Consumer Price Index (CPI)

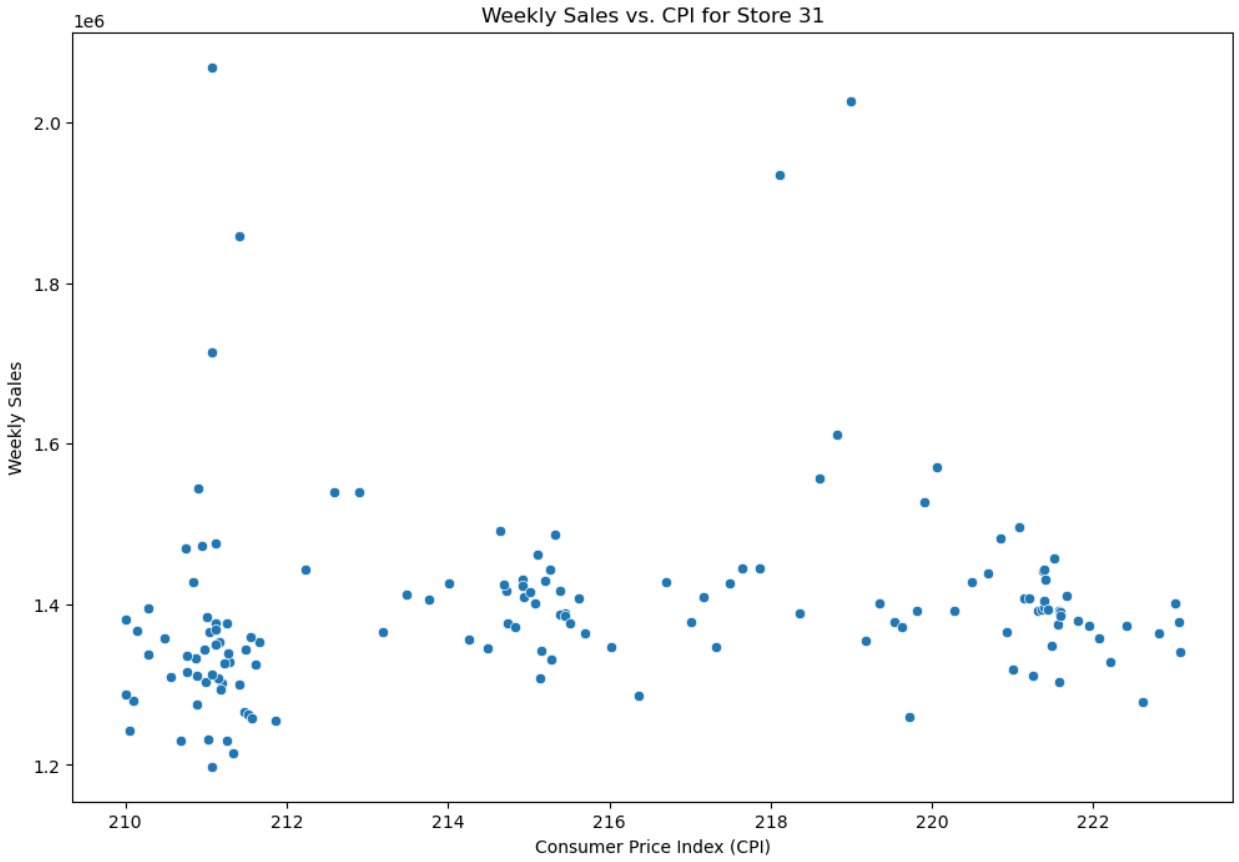

Weekly Sales vs. CPI for Store 26
1e6
1.6
1.5
1.4
1.3
1.2
1.1
1.0
0.9
0.8
Weekly Sales
132
133
134
135
136
137
138
139
Consumer Price Index (CPI)

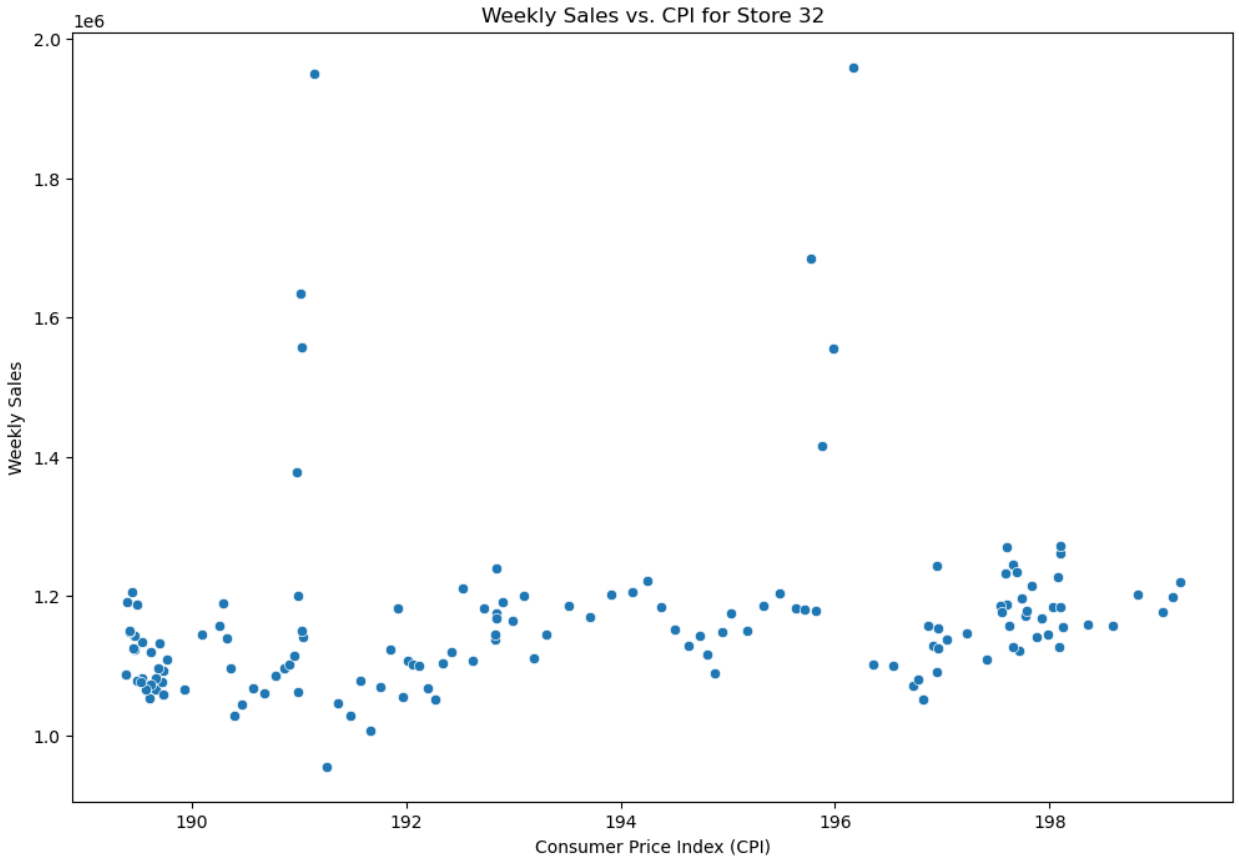

Weekly Sales vs. CPI for Store 27
1e6
3.00
2.75
2.50
2.25
2.00
1.75
1.50
1.25
Weekly Sales
135
136
137
138
139
140
141
142
143
Consumer Price Index (CPI)

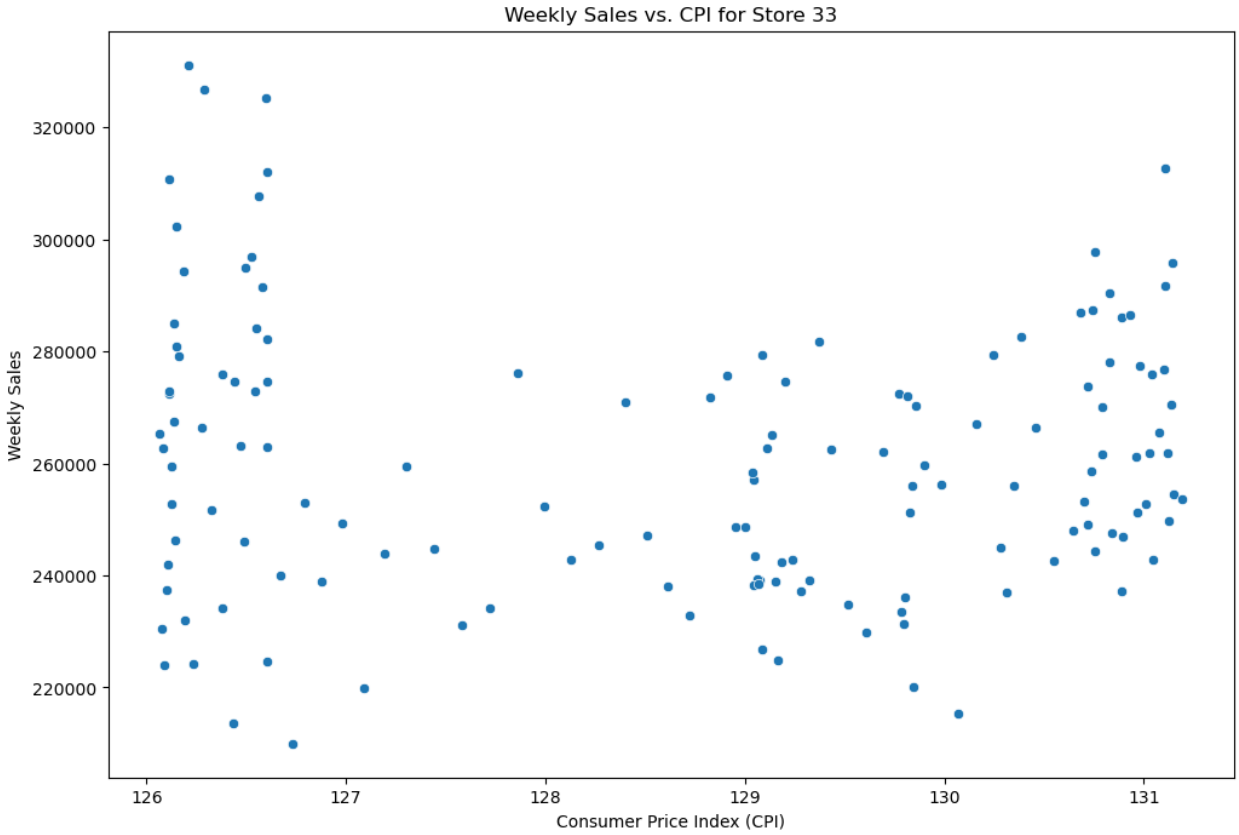

Weekly Sales vs. CPI for Store 28
1e6
2.0
1.8
1.6
1.4
1.2
Weekly Sales
126
127
128
129
130
131
Consumer Price Index (CPI)

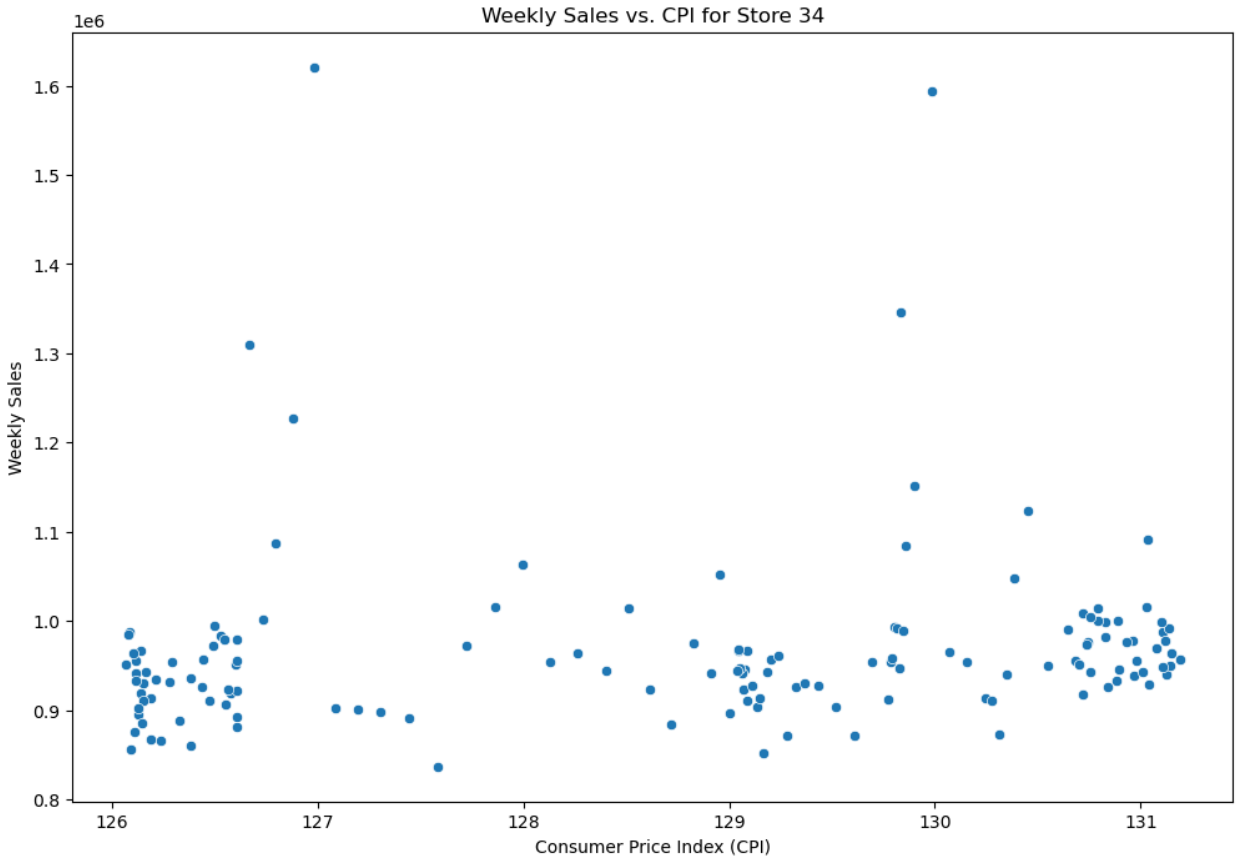

Weekly Sales vs. CPI for Store 29
1e6
1.1
1.0
0.9
0.8
0.7
0.6
0.5
0.4
Weekly Sales
132
133
134
135
136
137
138
139
Consumer Price Index (CPI)

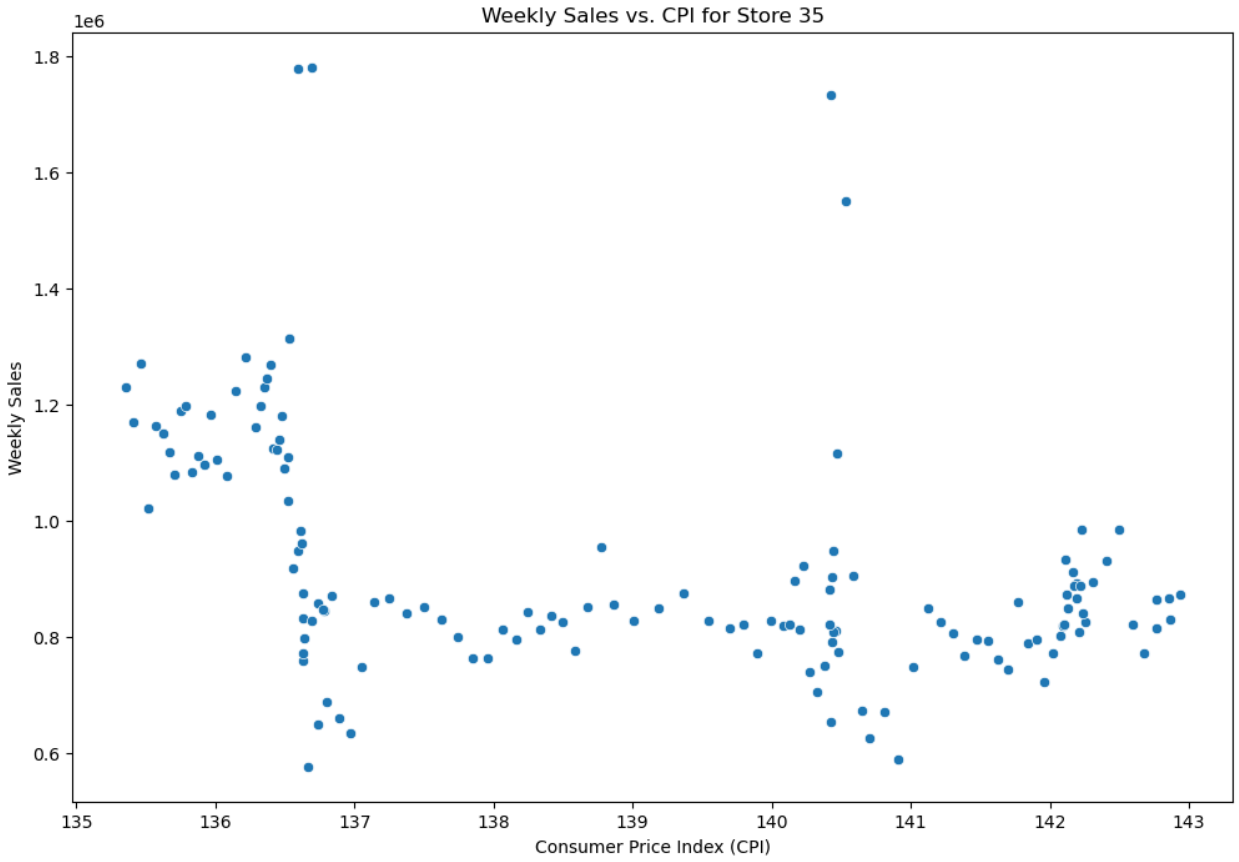

Weekly Sales vs. CPI for Store 30
Weekly Sales
520000
500000
480000
460000
440000
420000
400000
380000
210
212
214
216
218
220
222
Consumer Price Index (CPI)

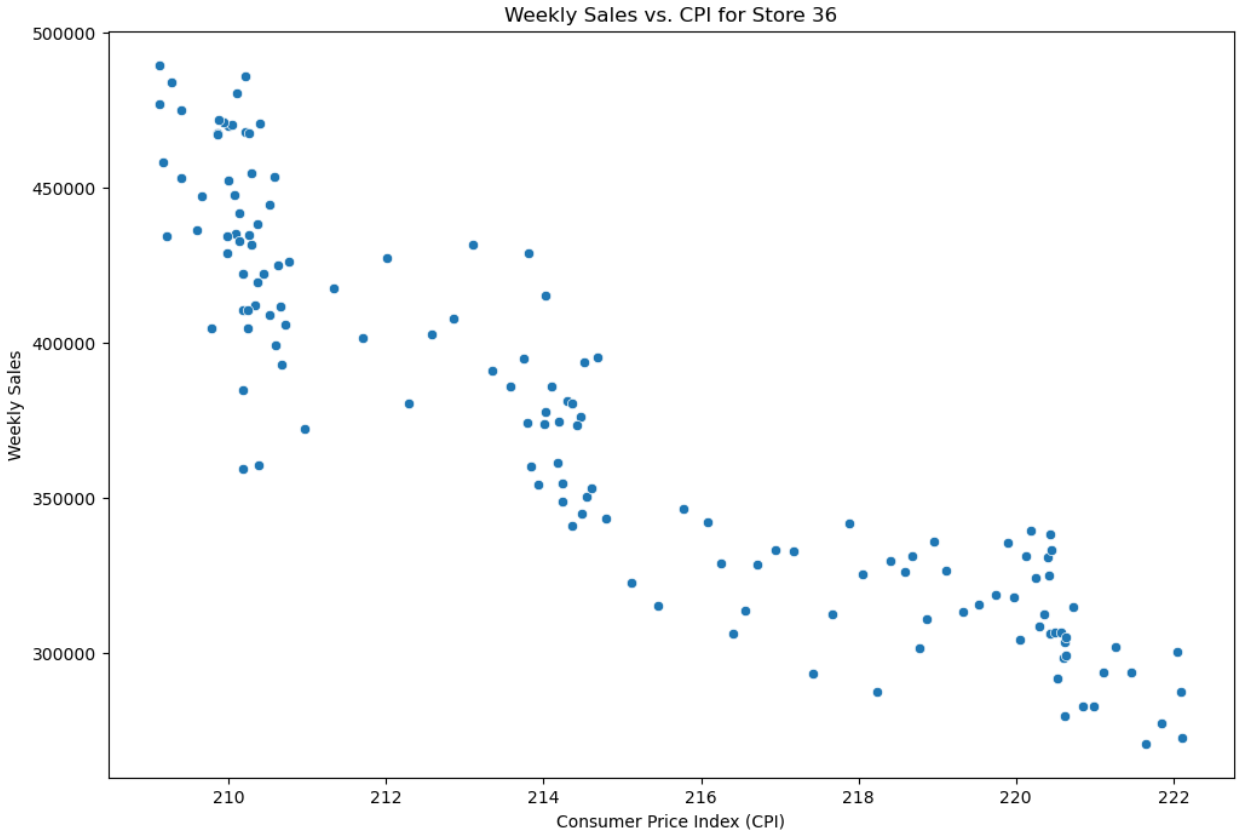

Weekly Sales vs. CPI for Store 31
1e6
2.0
1.8
1.6
1.4
1.2
Weekly Sales
210
212
214
216
218
220
222
Consumer Price Index (CPI)

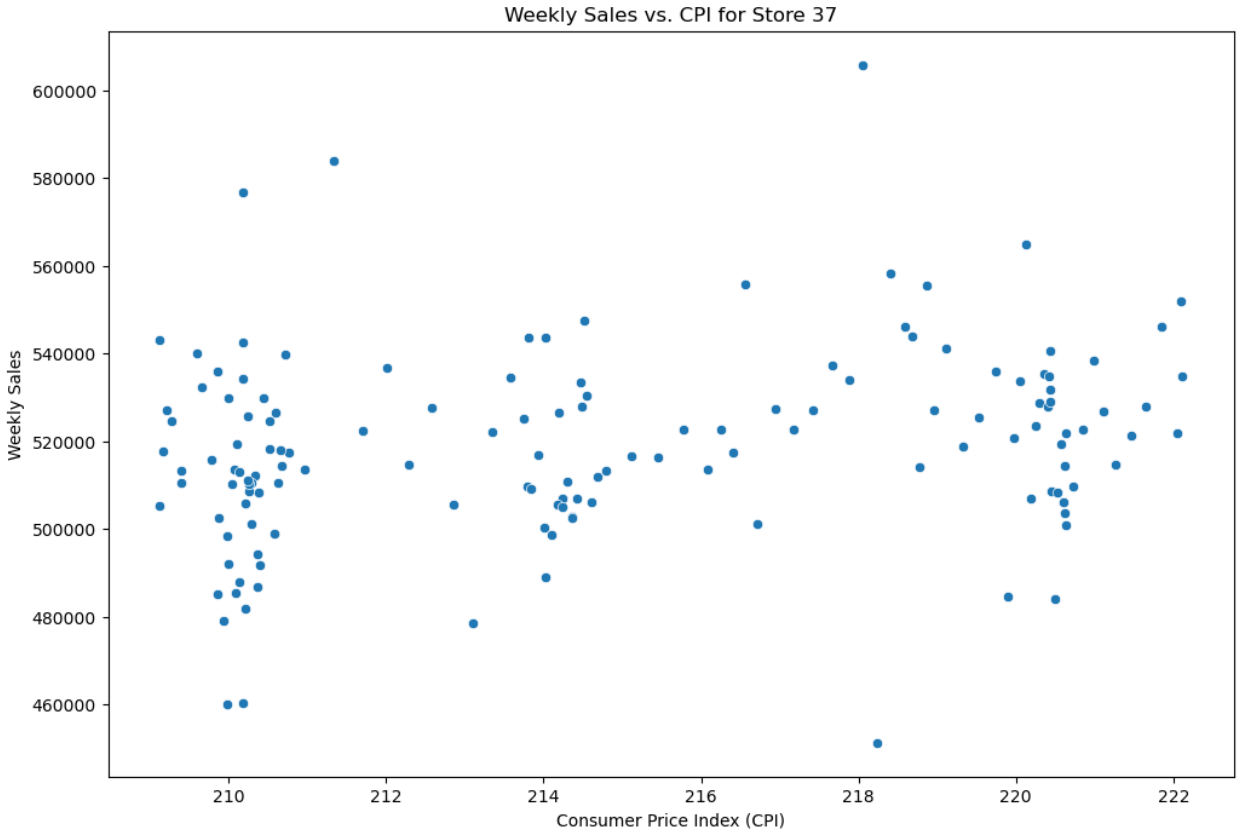

Weekly Sales vs. CPI for Store 32
1e6
2.0
1.8
1.6
1.4
1.2
1.0
Weekly Sales
190
192
194
196
198
Consumer Price Index (CPI)

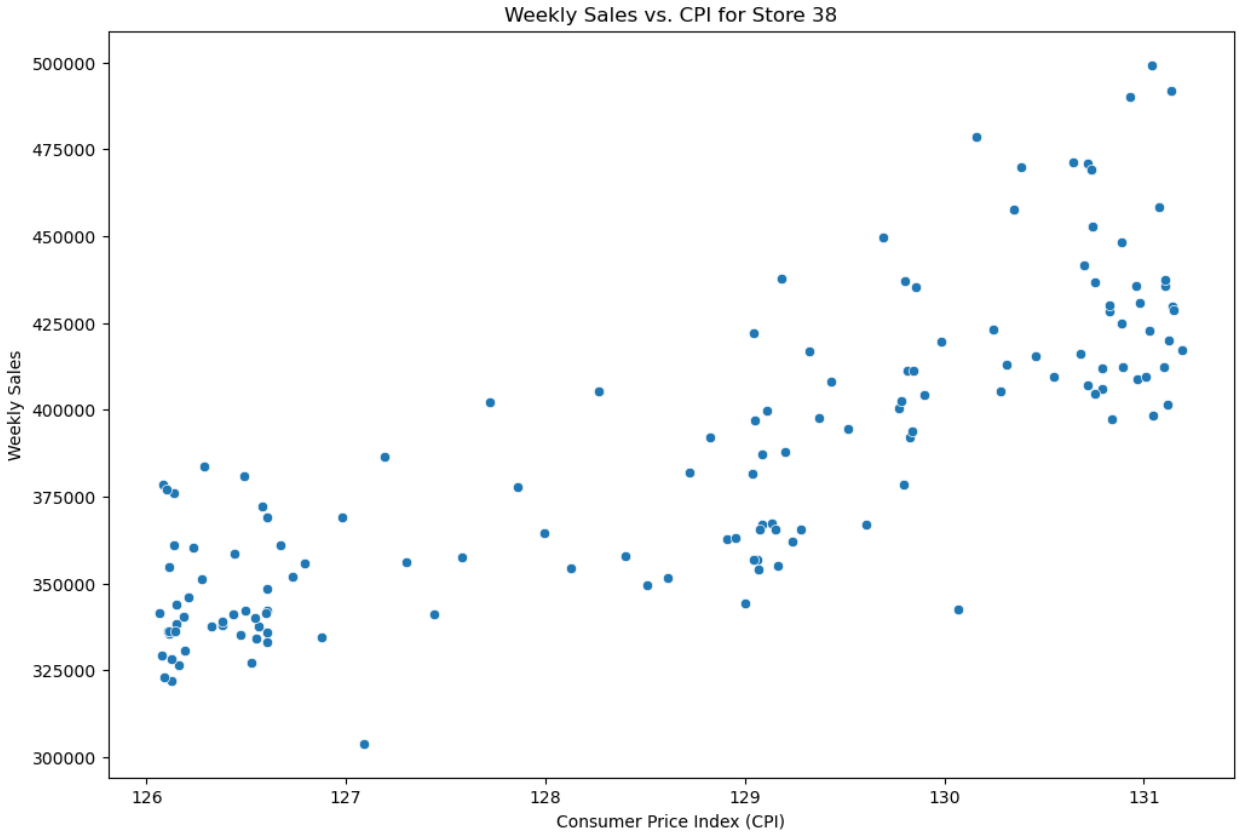

Weekly Sales vs. CPI for Store 33
Weekly Sales
320000
300000
280000
260000
240000
220000
126
127
128
129
130
131
Consumer Price Index (CPI)

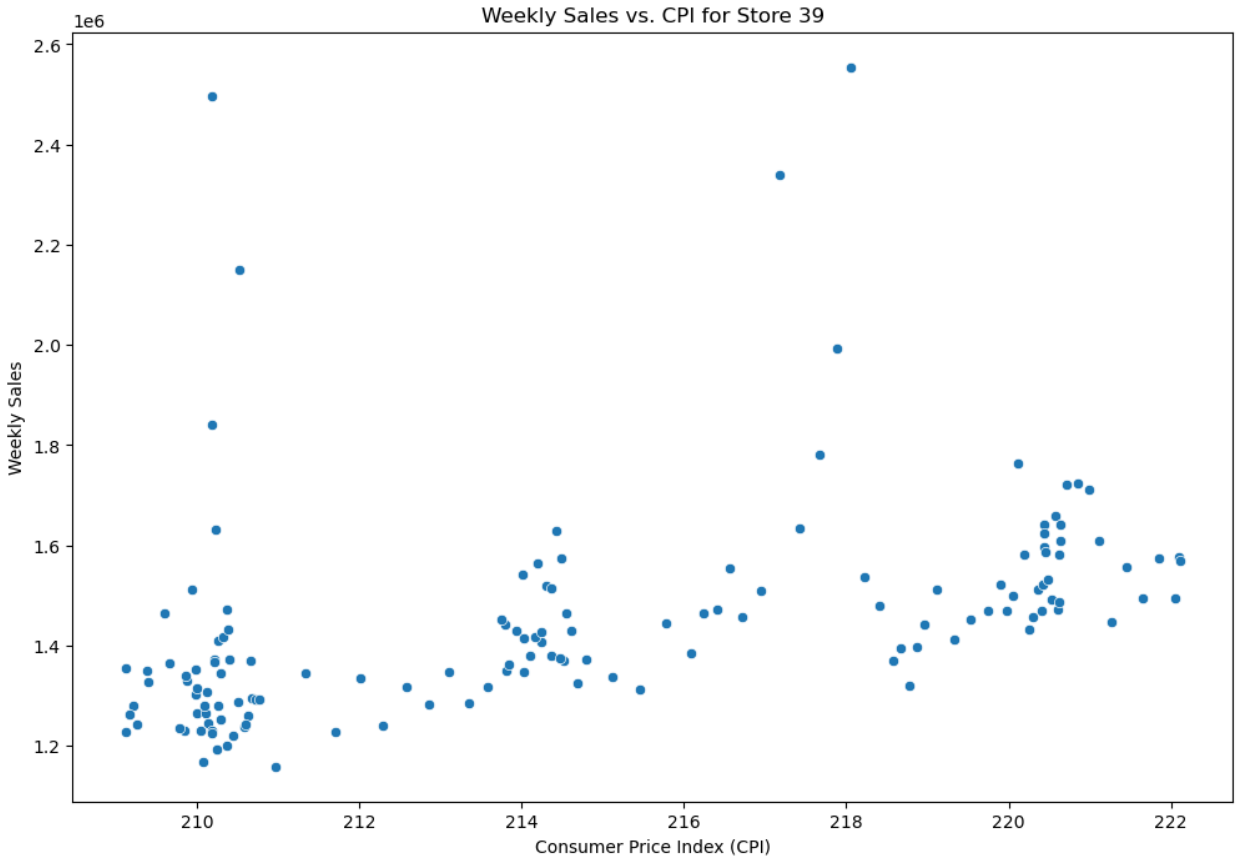

Weekly Sales vs. CPI for Store 34
1e6
1.6
1.5
1.4
1.3
1.2
1.1
1.0
0.9
0.8
Weekly Sales
126
127
128
129
130
131
Consumer Price Index (CPI)

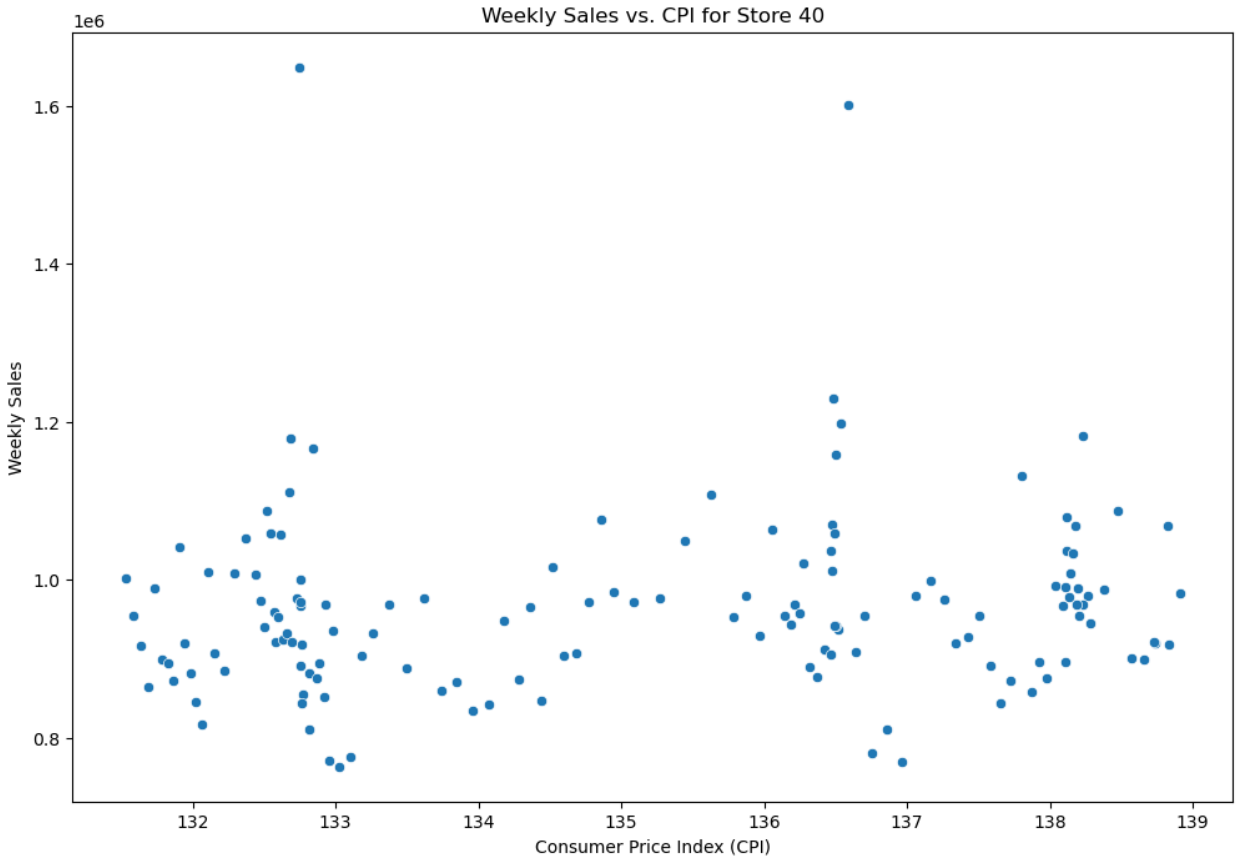

Weekly Sales vs. CPI for Store 35
1e6
1.8
1.6
1.4
1.2
1.0
0.8
0.6
Weekly Sales
135
136
137
138
139
140
141
142
143
Consumer Price Index (CPI)

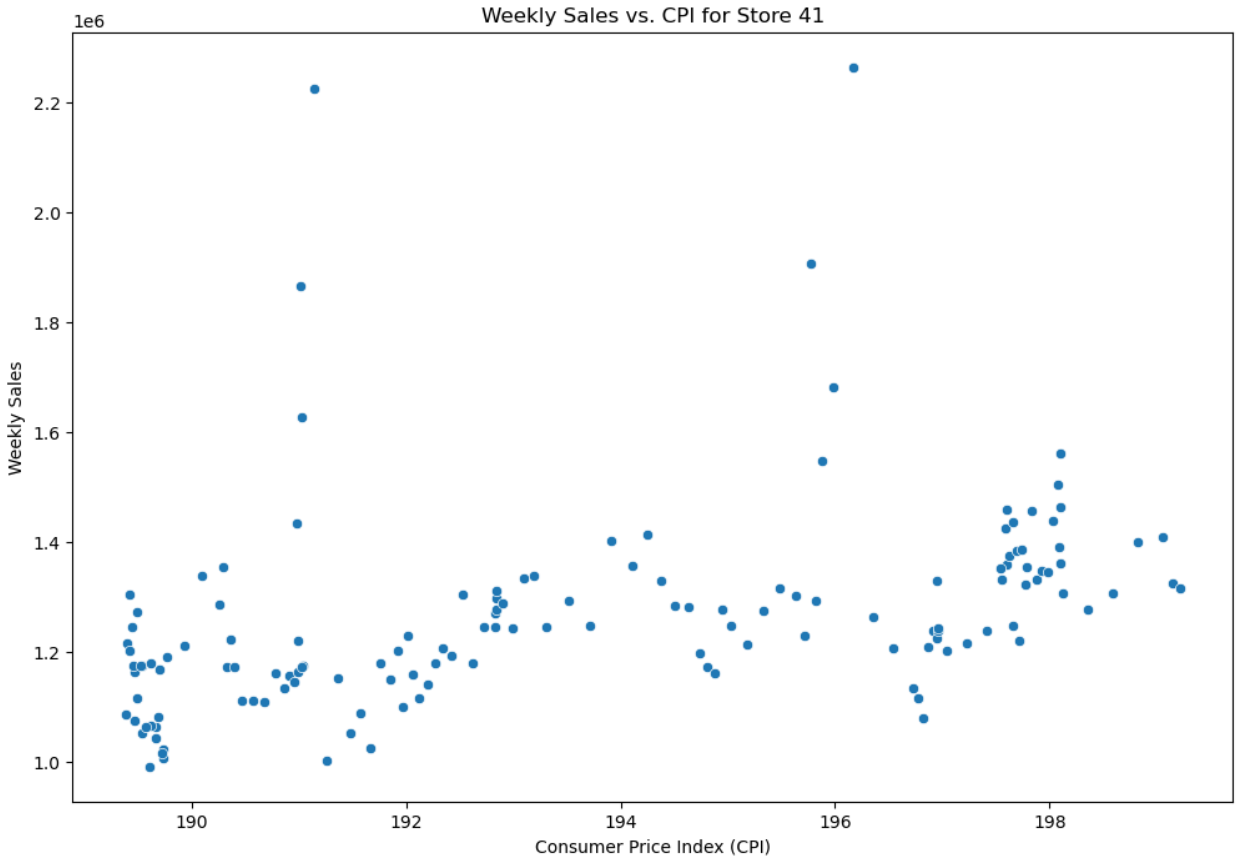

Weekly Sales vs. CPI for Store 36
Weekly Sales
500000
450000
400000
350000
300000
210
212
214
216
218
220
222
Consumer Price Index (CPI)

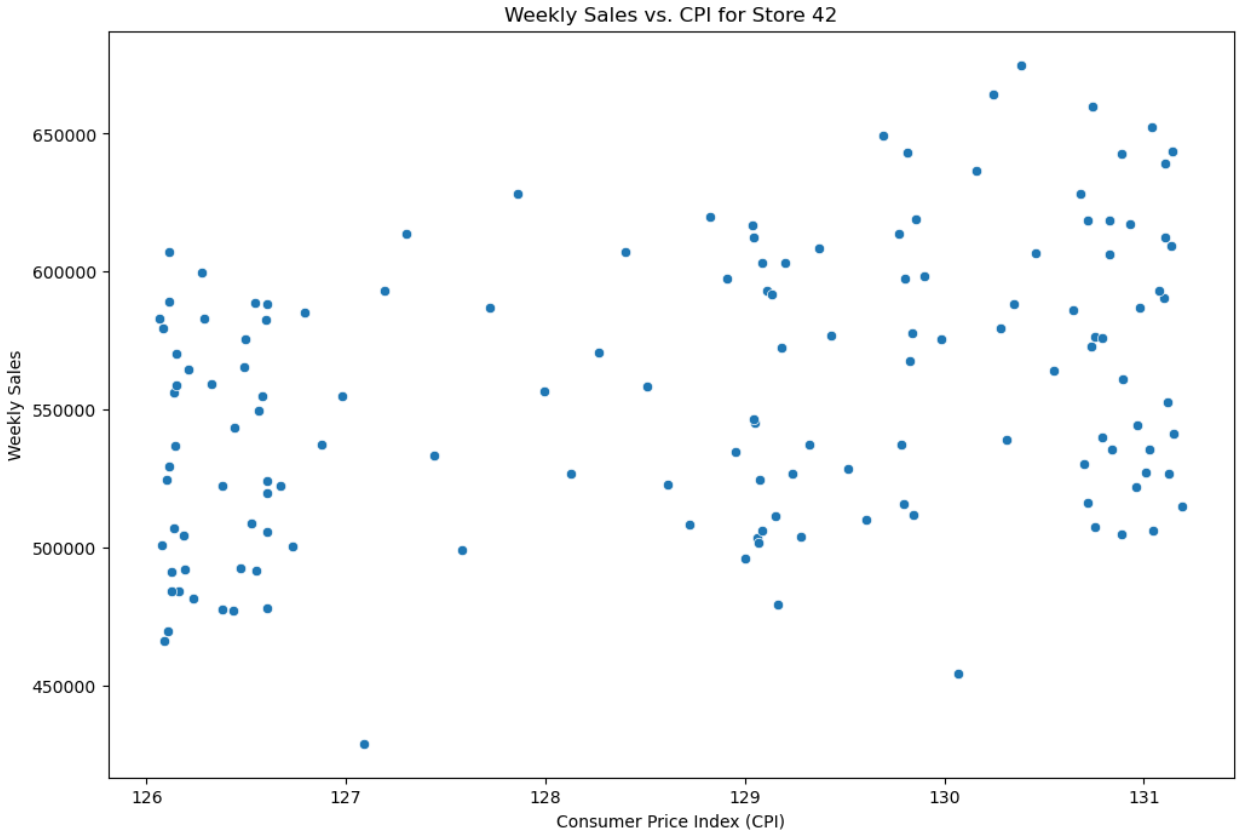

Weekly Sales vs. CPI for Store 37
Weekly Sales
600000
580000
560000
540000
520000
500000
480000
460000
210
212
214
216
218
220
222
Consumer Price Index (CPI)

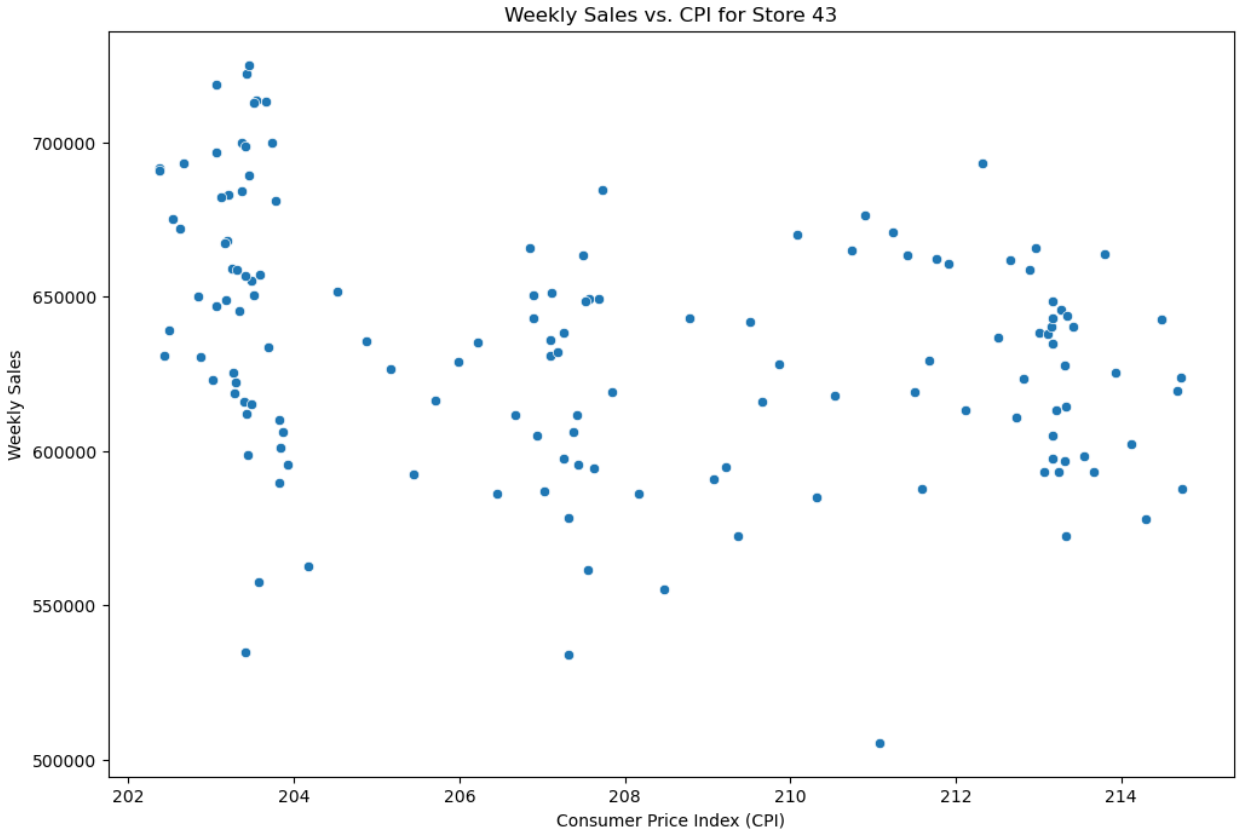

Weekly Sales vs. CPI for Store 38
Weekly Sales
500000
475000
450000
425000
400000
375000
350000
325000
300000
126
127
128
129
130
131
Consumer Price Index (CPI)

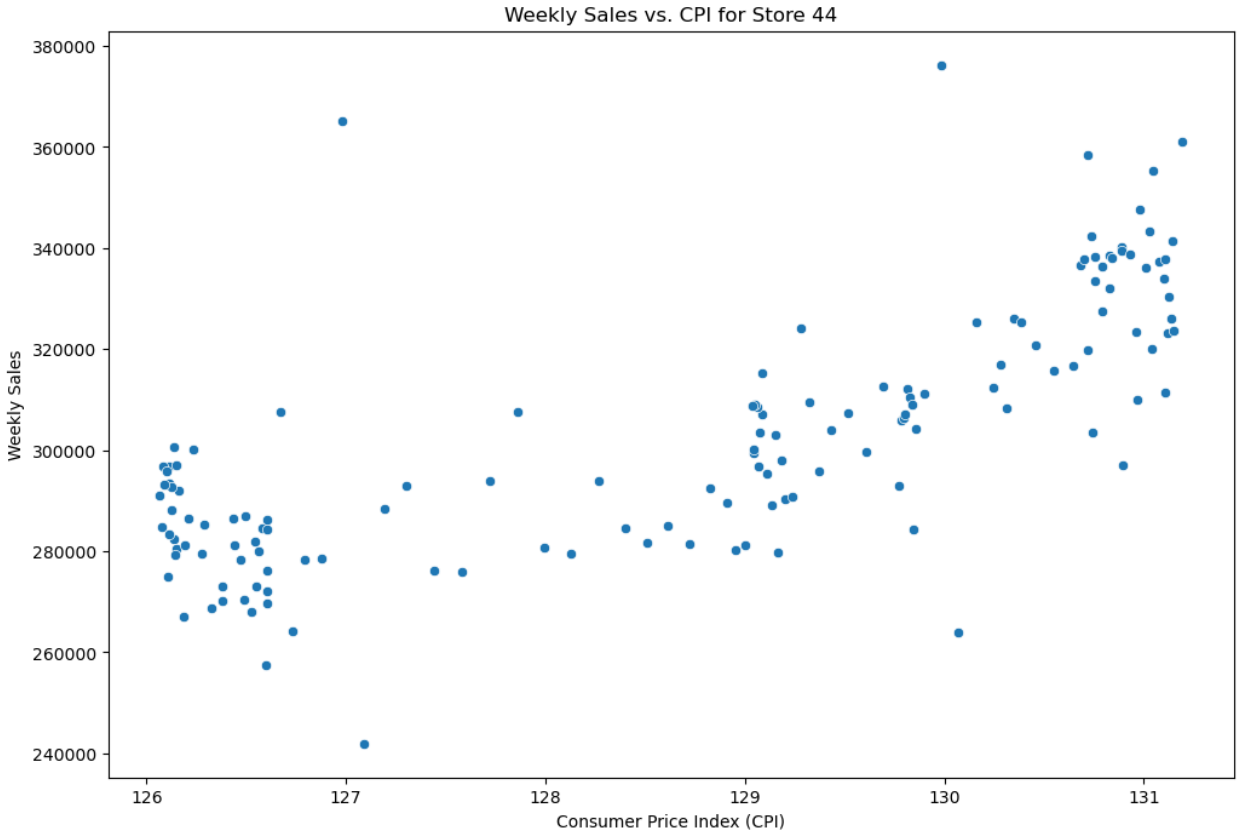

Weekly Sales vs. CPI for Store 39
1e6
2.6
2.4
2.2
2.0
1.8
1.6
1.4
1.2
Weekly Sales
210
212
214
216
218
220
222
Consumer Price Index (CPI)

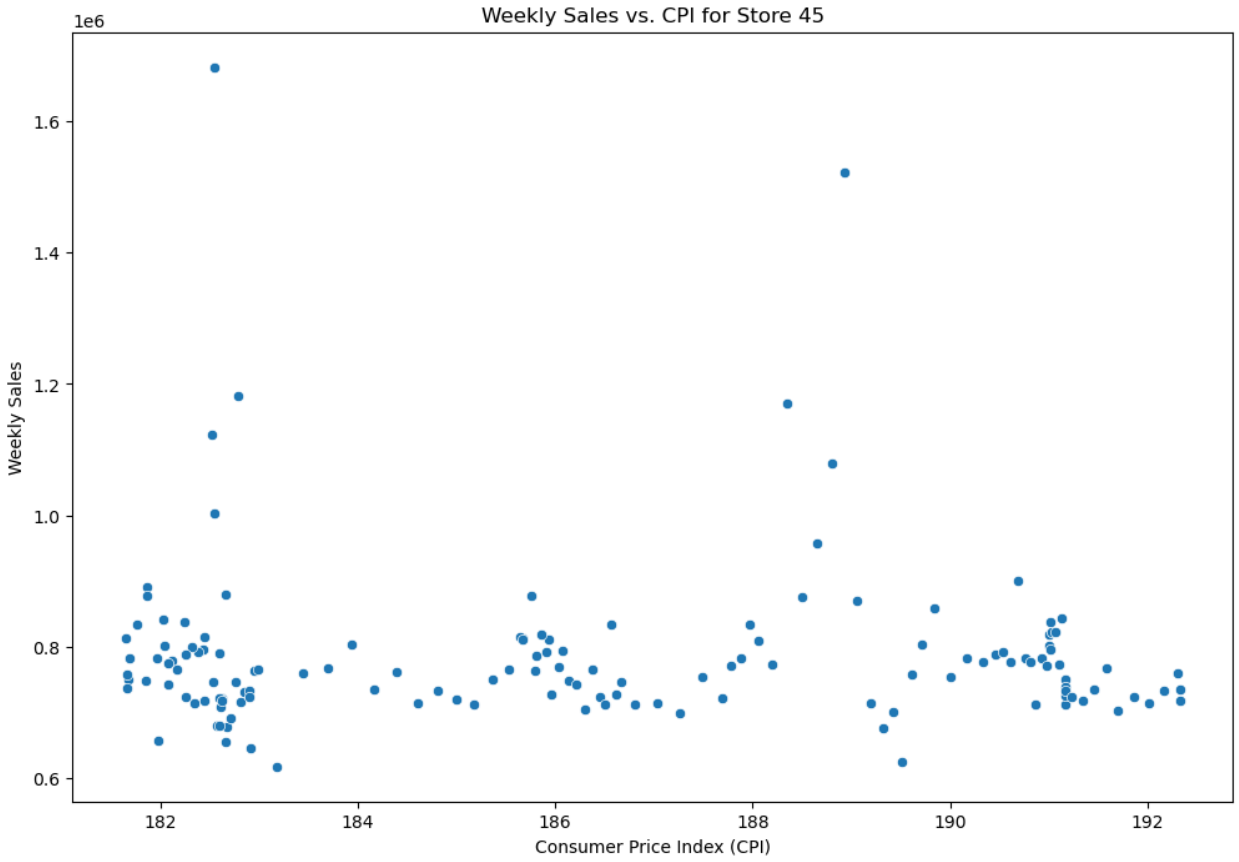

Weekly Sales vs. CPI for Store 40
1e6
1.6
1.4
1.2
1.0
0.8
Weekly Sales
132
133
134
135
136
137
138
139
Consumer Price Index (CPI)


Weekly Sales vs. CPI for Store 41
1e6
2.2
2.0
1.8
1.6
1.4
1.2
1.0
Weekly Sales
190
192
194
196
198
Consumer Price Index (CPI)


Weekly Sales vs. CPI for Store 42
650000
600000
550000
500000
450000
Weekly Sales
126
127
128
129
130
131
Consumer Price Index (CPI)


Weekly Sales vs. CPI for Store 43
700000
650000
600000
550000
500000
Weekly Sales
202
204
206
208
210
212
214
Consumer Price Index (CPI)


Weekly Sales vs. CPI for Store 44
Weekly Sales
380000
360000
340000
320000
300000
280000
260000
240000
126
127
128
129
130
131
Consumer Price Index (CPI)



Top performing stores according to the historical data.

```
store_sales = df.groupby('Store')['Weekly_Sales'].sum().reset_index()
top_stores =
store_sales.sort_values(by='Weekly_Sales',ascending=False)
top_stores.head(10)
```

```
    Store  Weekly_Sales
19     20  3.013978e+08
3       4  2.995440e+08
13     14  2.889999e+08
12     13  2.865177e+08
1       2  2.753824e+08
9      10  2.716177e+08
26     27  2.538559e+08
5       6  2.237561e+08
0       1  2.224028e+08
38     39  2.074455e+08
```

The worst performing store, and how significant is the difference between the highest and lowest performing stores

```
# grouping store and weekly_sales
store_sales = df.groupby('Store')['Weekly_Sales'].sum().reset_index()


# sorting values
sorted_store =
store_sales.sort_values(by='Weekly_Sales',ascending=False)

#highest value
best_store = sorted_store.iloc[0]

# worst value
worst_store = sorted_store.iloc[-1]

# difference between highest and worst value
sales_difference = best_store['Weekly_Sales'] -
worst_store['Weekly_Sales']

 # percentage of Weekly_sales
percentage_difference =
(sales_difference/best_store['Weekly_Sales'])*100

# Printing the Result

print(f"Highest Performing Store : {best_store['Store']} with Sales:
{best_store['Weekly_Sales']}")
print(f"Worst Performing Store :{worst_store['Store']} with Sales:
{worst_store['Weekly_Sales']}")
print(f"Difference in Sales :{sales_difference}")
print(f"Percent Difference :{percentage_difference:.2f}%")
```

```
Highest Performing Store : 20.0 with Sales: 301397792.46
Worst Performing Store :33.0 with Sales: 37160221.96
Difference in Sales :264237570.49999997
Percent Difference :87.67%
```

Use predictive modeling techniques to forecast the sales for each store for the next 12 weeks

```
!pip install prophet  # installing prophet
```

```
Requirement already satisfied: prophet in c:\users\vishal\anaconda3\
lib\site-packages (1.1.5)
Requirement already satisfied: cmdstanpy>=1.0.4 in c:\users\vishal\
```

```
anaconda3\lib\site-packages (from prophet) (1.2.4)
Requirement already satisfied: numpy>=1.15.4 in c:\users\vishal\
anaconda3\lib\site-packages (from prophet) (1.26.4)
Requirement already satisfied: matplotlib>=2.0.0 in c:\users\vishal\
anaconda3\lib\site-packages (from prophet) (3.8.0)
Requirement already satisfied: pandas>=1.0.4 in c:\users\vishal\
anaconda3\lib\site-packages (from prophet) (2.1.4)
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anaconda3\lib\site-packages (from prophet) (0.56)
Requirement already satisfied: tqdm>=4.36.1 in c:\users\vishal\
anaconda3\lib\site-packages (from prophet) (4.65.0)
Requirement already satisfied: importlib-resources in c:\users\vishal\
anaconda3\lib\site-packages (from prophet) (6.4.5)
Requirement already satisfied: stanio<2.0.0,>=0.4.0 in c:\users\
vishal\anaconda3\lib\site-packages (from cmdstanpy>=1.0.4->prophet)
(0.5.1)
Requirement already satisfied: python-dateutil in c:\users\vishal\
anaconda3\lib\site-packages (from holidays>=0.25->prophet) (2.8.2)
Requirement already satisfied: contourpy>=1.0.1 in c:\users\vishal\
anaconda3\lib\site-packages (from matplotlib>=2.0.0->prophet) (1.2.0)
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anaconda3\lib\site-packages (from matplotlib>=2.0.0->prophet) (0.11.0)
Requirement already satisfied: fonttools>=4.22.0 in c:\users\vishal\
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Requirement already satisfied: kiwisolver>=1.0.1 in c:\users\vishal\
anaconda3\lib\site-packages (from matplotlib>=2.0.0->prophet) (1.4.4)
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anaconda3\lib\site-packages (from matplotlib>=2.0.0->prophet) (10.2.0)
Requirement already satisfied: pyparsing>=2.3.1 in c:\users\vishal\
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anaconda3\lib\site-packages (from pandas>=1.0.4->prophet)
(2023.3.post1)
Requirement already satisfied: tzdata>=2022.1 in c:\users\vishal\
anaconda3\lib\site-packages (from pandas>=1.0.4->prophet) (2023.3)
Requirement already satisfied: colorama in c:\users\vishal\anaconda3\
lib\site-packages (from tqdm>=4.36.1->prophet) (0.4.6)
Requirement already satisfied: six>=1.5 in c:\users\vishal\anaconda3\
lib\site-packages (from python-dateutil->holidays>=0.25->prophet)
(1.16.0)
```

```
# Convertint the 'Date' column to datetime format
df['Date'] = pd.to_datetime(df['Date'], dayfirst=True)

# Preparing data for Prophet
prophet_data = df[df['Store'] == 1][['Date',
'Weekly_Sales']].rename(columns={'Date': 'ds', 'Weekly_Sales': 'y'})
```

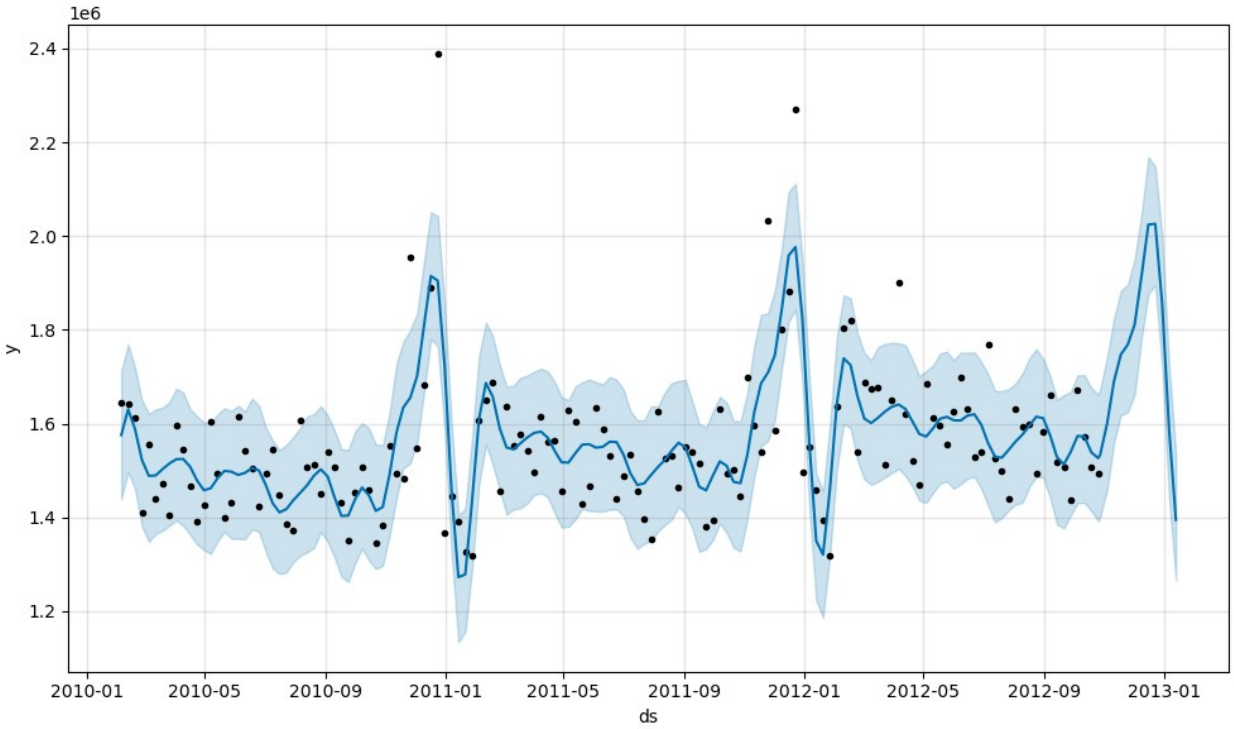
```
# Initializing and fitting the model
prophet_model = Prophet()
prophet_model.fit(prophet_data)

# Forecasting the next 12 weeks
future = prophet_model.make_future_dataframe(periods=12, freq='W')  # 
Next 12 weeks
forecast = prophet_model.predict(future)

# Ploting the forecast
prophet_model.plot(forecast)
plt.show()

# Output
forecast[['ds', 'yhat']].tail(12)
```

```
09:31:10 - cmdstanpy - INFO - Chain [1] start processing
09:31:10 - cmdstanpy - INFO - Chain [1] done processing
C:\Users\vishal\anaconda3\Lib\site-packages\prophet\plot.py:72: 
FutureWarning: The behavior of DatetimeProperties.to_pydatetime is 
deprecated, in a future version this will return a Series containing 
python datetime objects instead of an ndarray. To retain the old 
behavior, call `np.array` on the result
  fcst_t = fcst['ds'].dt.to_pydatetime()
C:\Users\vishal\anaconda3\Lib\site-packages\prophet\plot.py:73: 
FutureWarning: The behavior of DatetimeProperties.to_pydatetime is 
deprecated, in a future version this will return a Series containing 
python datetime objects instead of an ndarray. To retain the old 
behavior, call `np.array` on the result
  ax.plot(m.history['ds'].dt.to_pydatetime(), m.history['y'], 'k.',
```



	ds	yhat
143	2012-10-28	1.533718e+06
144	2012-11-04	1.599962e+06
145	2012-11-11	1.690150e+06
146	2012-11-18	1.747218e+06
147	2012-11-25	1.768332e+06
148	2012-12-02	1.810907e+06
149	2012-12-09	1.913990e+06
150	2012-12-16	2.024511e+06
151	2012-12-23	2.026083e+06
152	2012-12-30	1.856230e+06
153	2013-01-06	1.590304e+06
154	2013-01-13	1.394517e+06