In [42]:
```
import scipy as sp
import scipy.stats as stats
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
import copy
# Set color map to have light blue background
sns.set()
import statsmodels.formula.api as smf
import statsmodels.api as sm
from sklearn.model_selection import train_test_split
%matplotlib inline
```

Purpose of the Project

The goal of this project is to analyze, through supervised learning, any kinds of relations between monthly average urban Consumer Price Index, price of grocery items, and time in the United States. I will be using singular and multiple linear regression through Ordinary Least Squares to predict causal relationships between individual grocery items, the monthly CPI, and the months and years that each of these attributes are being evaluated.

I will be using data from the Federal Reserve Economic Data (FRED) Site from the St. Louis Federal Reserve Branch, which has more than 100 years of financial data on the average monthly price of bread, milk, etc. The goal of the project is to evaluate what effects that raising the prices of grocery items have become in response to raising the urban Consumer Price Index (CPI) on urban areas in the United States. The data collected and cleaned is based on a rolling monthly average.

About the Data

The datasets are compilations of grocery items' monthly average prices in urban areas of the United States.

There were some empty data points with each of the CSV files that I was working with, but they have been edited to make sure that any empty values were filled or removed accordingly. There were six CSV files combined into one CSV file containing all of the columns of average grocery items' prices. The dates were also reformatted in the CSV files using Microsoft Excel where the dates, initially listed in its respective column in the form **M/D/YYYY** are now listed in the form **YYYY-MM-DD**.

There are seven columns, one of which is a date consisting of a month and year. By default, the day of the month had already been preset by FRED to the first day of each month for 300 months, or 25 years, from February 1999 to February 2024, which was the last month of recorded data on monthly average urban prices.

The grocery items being compared and run through for modeling are: white bread, ground beef, eggs, whole milk, and bananas. Another column, urban_cpi, is the average urban Consumer Price Index (CPI) for spending on groceries in urban US areas.

Data Preparation

All data editing and preparation was done prior to evaluating and/or modeling on any of its contents using Microsoft Excel. For each of the grocery items being evaluated and inputted for modeling, collections of monthly average prices began as early as 1985 for items. The monthly average urban CPI had data collected since January 1913.

Since the analysis and modeling are for patterns and trends in the last 25 years, original files were modified and redacted to only present data for all six attributes listed above from February 1999 to February 2024.

Supervised Learning Models Used

In this analysis, I will use linear regression modeling with Ordinary Least-Squares (OLS) Regression. This will be done by using the `statsmodels` library in Python with `ols` .

In [43]:

```python
# Call the CSV file and read it. Then return its basic structural info.
groceries_df = pd.read_csv("fred_groceries_021999_022024.csv", encoding='utf-8')
groceries_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 301 entries, 0 to 300
Data columns (total 7 columns):
 #   Column       Non-Null Count  Dtype  
---  ------       --------------  -----  
 0   DATE         301 non-null    object 
 1   white_bread  301 non-null    float64
 2   ground_beef  301 non-null    float64
 3   egg          301 non-null    float64
 4   whole_milk   301 non-null    float64
 5   banana       301 non-null    float64
 6   urban_cpi    301 non-null    float64
dtypes: float64(6), object(1)
memory usage: 16.6+ KB
```

In [44]:

```python
# groceries_df.urban_cpi
```

In [45]:

```python
# Add a column for signifying the number of each month (300 in total)
month= np.arange(0, len(groceries_df.DATE), 1, dtype=int)
# month
groceries_df['month_number'] = month
groceries_df['month_number'].head()
```

Out[45]:

```
0    0
1    1
2    2
3    3
4    4
Name: month_number, dtype: int32
```

In [46]:
```
# To refresh, these are the descriptive statistics of the table
groceries_df.describe()
```

Out[46]:

	white_bread	ground_beef	egg	whole_milk	banana	urban_cpi	month_number
count	301.000000	301.000000	301.000000	301.000000	301.000000	301.000000	301.000000
mean	1.297900	2.999774	1.651575	3.289449	0.561970	227.267920	150.000000
std	0.258624	1.078457	0.579640	0.392196	0.049593	42.223027	87.035433
min	0.878000	0.000000	0.838000	2.656000	0.469000	163.300000	0.000000
25%	1.046000	2.196000	1.257000	2.964000	0.509000	190.400000	75.000000
50%	1.358000	2.818000	1.599000	3.241000	0.574000	229.554000	150.000000
75%	1.419000	3.841000	1.920000	3.557000	0.601000	251.238000	225.000000
max	2.033000	5.353000	4.823000	4.218000	0.643000	327.731000	300.000000

In [47]:
```
# Perform single linear regresssion on each of the columns
# with respect to Average Urban Consumer Price Index in US
# Create X, y variables

X = sm.add_constant(groceries_df)
y = groceries_df['urban_cpi']

# Create train and test data splits, 80-20 split
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size = 0.2, random_
```

In [48]:
```
# Get shapes of X, y
print(X.shape, y.shape)
```

```
(301, 9) (301,)
```

In [49]:
```
# Get shapes of X_train, X_test, y_train, y_test

print(X_train.shape, X_test.shape, y_train.shape, y_test.shape)
```

```
(240, 9) (61, 9) (240,) (61,)
```

In [50]:
```
# Get the linear regression model summary
# using Ordinary Linear Squares (OLS) from statsmodels

lr_model = smf.ols(formula="urban_cpi ~ white_bread", data=X_train).fit()
lr_model.summary()
```

Out[50]:

OLS Regression Results

Dep. Variable:	urban_cpi	**R-squared:**	0.878
Model:	OLS	**Adj. R-squared:**	0.877
Method:	Least Squares	**F-statistic:**	1705.
Date:	Tue, 30 Apr 2024	**Prob (F-statistic):**	1.69e-110
Time:	10:36:45	**Log-Likelihood:**	-991.25
No. Observations:	240	**AIC:**	1986.
Df Residuals:	238	**BIC:**	1993.
Df Model:	1		
Covariance Type:	nonrobust		

	coef	**std err**	**t**	**P>|t|**	**[0.025**	**0.975]**
Intercept	29.1750	4.895	5.961	0.000	19.533	38.817
white_bread	152.2903	3.688	41.290	0.000	145.024	159.556

Omnibus:	8.429	**Durbin-Watson:**	2.159
Prob(Omnibus):	0.015	**Jarque-Bera (JB):**	8.079
Skew:	0.400	**Prob(JB):**	0.0176
Kurtosis:	2.590	**Cond. No.**	10.3

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

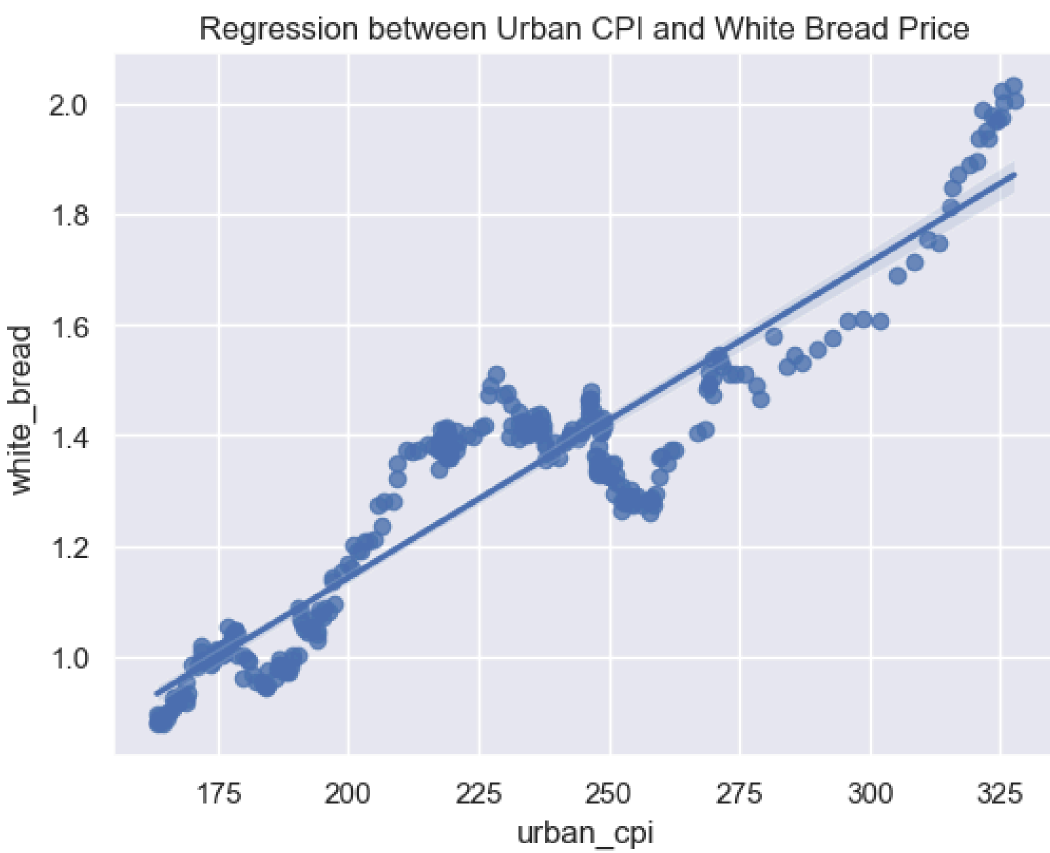
In [51]:
```
# Predict the values of CPI on white bread price
# then compare to the actual CPI values

lr_preds = lr_model.predict(X_test)
lr_preds
```

Out[51]:
```
223    234.614584
150    253.650872
226    229.589004
296    334.060152
52     175.525946
          ...
137    236.289777
227    224.258843
26     182.683590
106    224.106553
92     196.237427
Length: 61, dtype: float64
```

In [52]:
```
lr_model.fittedvalues
```

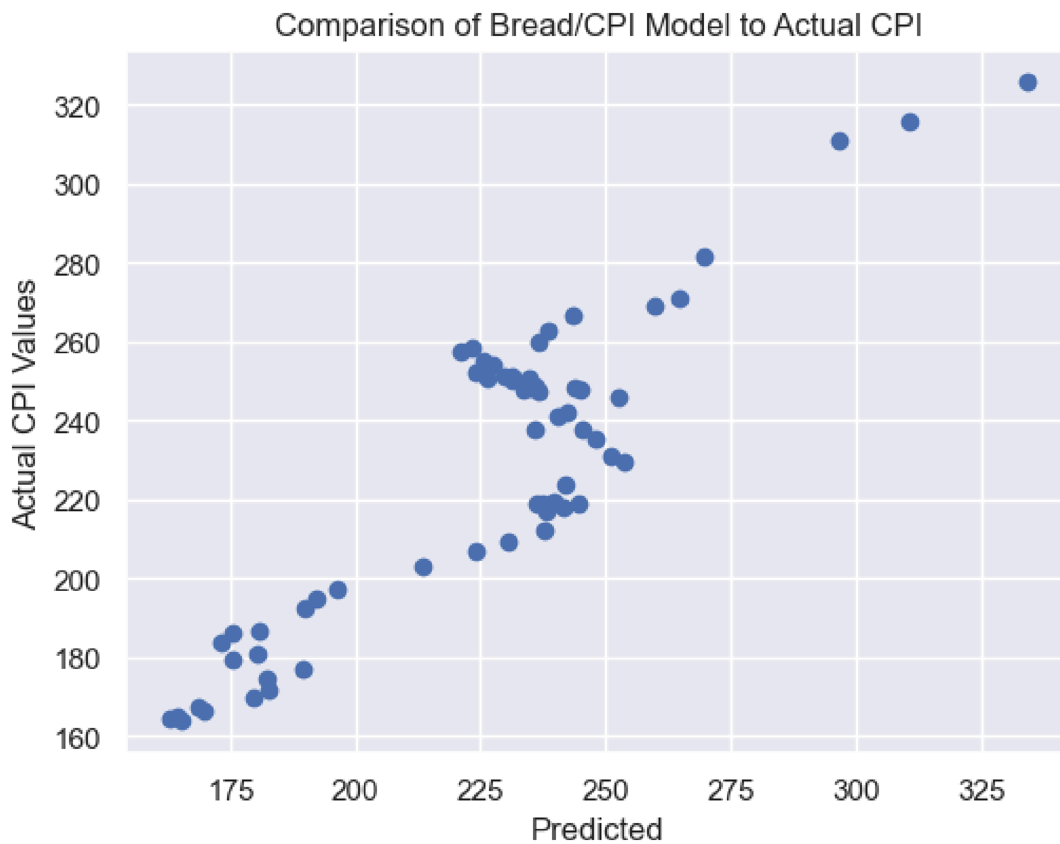
Out[52]:
```
74     182.074429
239    223.192811
64     178.267172
294    329.186863
286    314.414703
          ...
251    234.919165
192    247.711550
117    238.878713
47     187.861461
172    248.320711
Length: 240, dtype: float64
```

In [53]:
```
# Regression plot between urban CPI and white bread price

sns.regplot(x='urban_cpi', y='white_bread', data=groceries_df)
plt.title("Regression between Urban CPI and White Bread Price")
plt.show()
```



In [56]:

```
# Make a scatter plot of the predicted CPI values (x) compared to the actual liste

plt.scatter(lr_preds, y_test)
plt.title("Comparison of Bread/CPI Model to Actual CPI")
plt.xlabel("Predicted")
plt.ylabel("Actual CPI Values")
plt.show()
```



In [ ]:

```
 
```

In [ ]:

```
 
```

In [14]:
```
# Single linear regression (OLS) between urban CPI and price of ground beef on X_t
lr_model_beef = smf.ols(formula="urban_cpi ~ ground_beef", data=X_train).fit()
lr_model_beef.summary()
```

Out[14]:

OLS Regression Results

Dep. Variable:	urban_cpi	**R-squared:**	0.895
Model:	OLS	**Adj. R-squared:**	0.895
Method:	Least Squares	**F-statistic:**	2038.
Date:	Tue, 30 Apr 2024	**Prob (F-statistic):**	1.11e-118
Time:	10:34:49	**Log-Likelihood:**	-972.26
No. Observations:	240	**AIC:**	1949.
Df Residuals:	238	**BIC:**	1955.
Df Model:	1		
Covariance Type:	nonrobust		

	coef	**std err**	**t**	**P>|t|**	**[0.025**	**0.975]**
Intercept	116.0974	2.621	44.289	0.000	110.933	121.261
ground_beef	37.0788	0.821	45.144	0.000	35.461	38.697

Omnibus:	182.554	**Durbin-Watson:**	1.982
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	4529.403
Skew:	2.633	**Prob(JB):**	0.00
Kurtosis:	23.621	**Cond. No.**	10.1

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

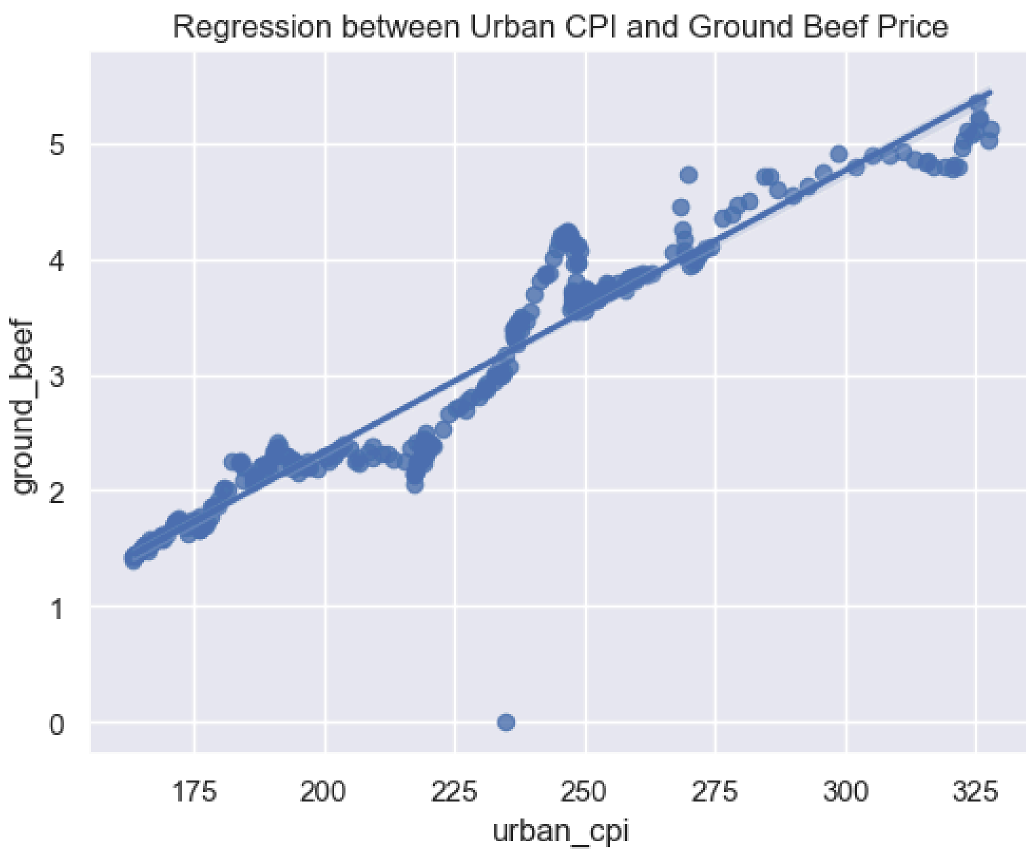
In [15]:
```
lr_preds_beef = lr_model_beef.predict(X_test)
lr_preds_beef
```

Out[15]:
```
223    253.548465
150    220.622491
226    253.585544
296    309.871161
52     187.733596
          ...
137    207.051651
227    251.101264
26     181.467279
106    198.931394
92     197.893187
Length: 61, dtype: float64
```

In [16]:
```
lr_model_beef.fittedvalues
```

Out[16]:
```
74     201.712304
239    257.033872
64     193.147101
294    304.309341
286    294.075593
          ...
251    260.185570
192    273.237308
117    203.492086
47     179.947048
172    241.497855
Length: 240, dtype: float64
```

In [17]:
```
sns.regplot(x='urban_cpi', y='ground_beef', data=groceries_df)
plt.title("Regression between Urban CPI and Ground Beef Price")
plt.show()
```



In [ ]:
```

```

In [ ]:
```

```

In [ ]:
```

```

In [ ]:
```

```

In [18]:
```
lr_model_egg = smf.ols(formula="urban_cpi ~ egg", data=X_train).fit()
lr_model_egg.summary()
```

Out[18]:

OLS Regression Results

Dep. Variable:	urban_cpi	**R-squared:**	0.551
Model:	OLS	**Adj. R-squared:**	0.549
Method:	Least Squares	**F-statistic:**	291.8
Date:	Tue, 30 Apr 2024	**Prob (F-statistic):**	3.08e-43
Time:	10:34:49	**Log-Likelihood:**	-1147.2
No. Observations:	240	**AIC:**	2298.
Df Residuals:	238	**BIC:**	2305.
Df Model:	1		
Covariance Type:	nonrobust		

	coef	**std err**	**t**	**P>|t|**	**[0.025**	**0.975]**
Intercept	138.4136	5.525	25.053	0.000	127.530	149.297
egg	53.4937	3.132	17.081	0.000	47.324	59.663

Omnibus:	19.382	**Durbin-Watson:**	2.101
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	22.551
Skew:	0.748	**Prob(JB):**	1.27e-05
Kurtosis:	2.869	**Cond. No.**	6.75

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

In [19]:
```
lr_preds_egg = lr_model_egg.predict(X_test)
lr_preds_egg
```

Out[19]:
```
223    214.481638
150    229.941320
226    235.504666
296    249.252550
52     202.552540
          ...
137    215.498018
227    233.043955
26     193.405116
106    250.696880
92     205.655175
Length: 61, dtype: float64
```

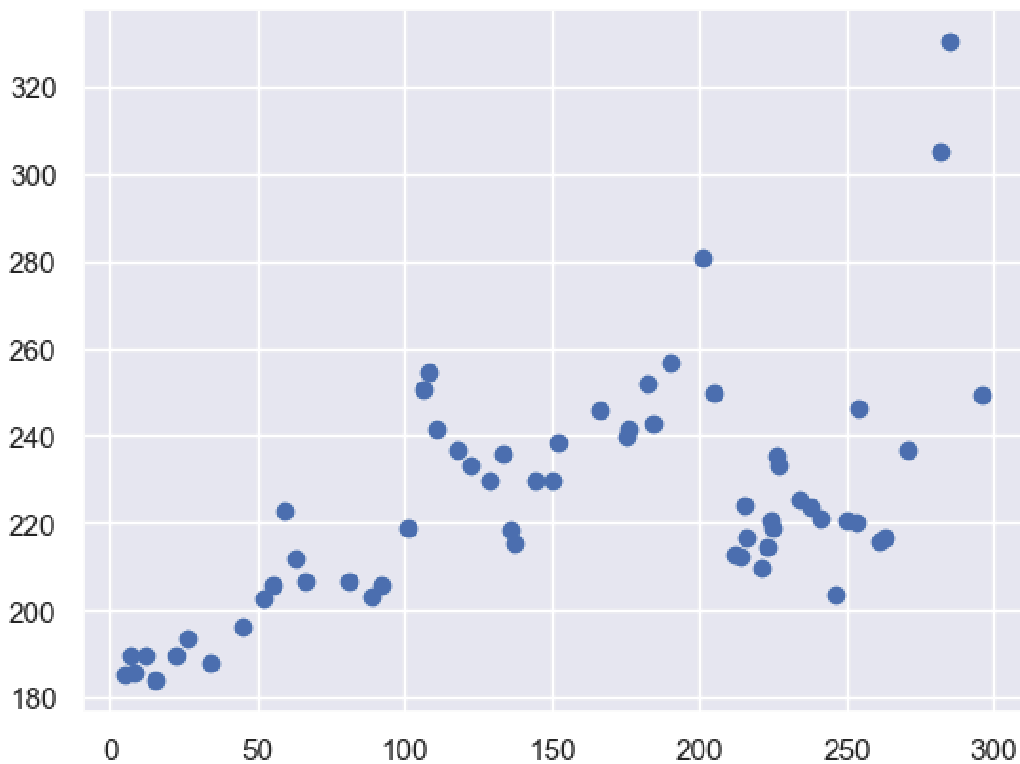
In [20]:
```
lr_model_egg.fittedvalues
```

Out[20]:
```
74     200.680260
239    221.542808
64     208.543836
294    247.701232
286    365.761852
          ...
251    216.567892
192    250.108449
117    236.735021
47     201.268691
172    237.858389
Length: 240, dtype: float64
```

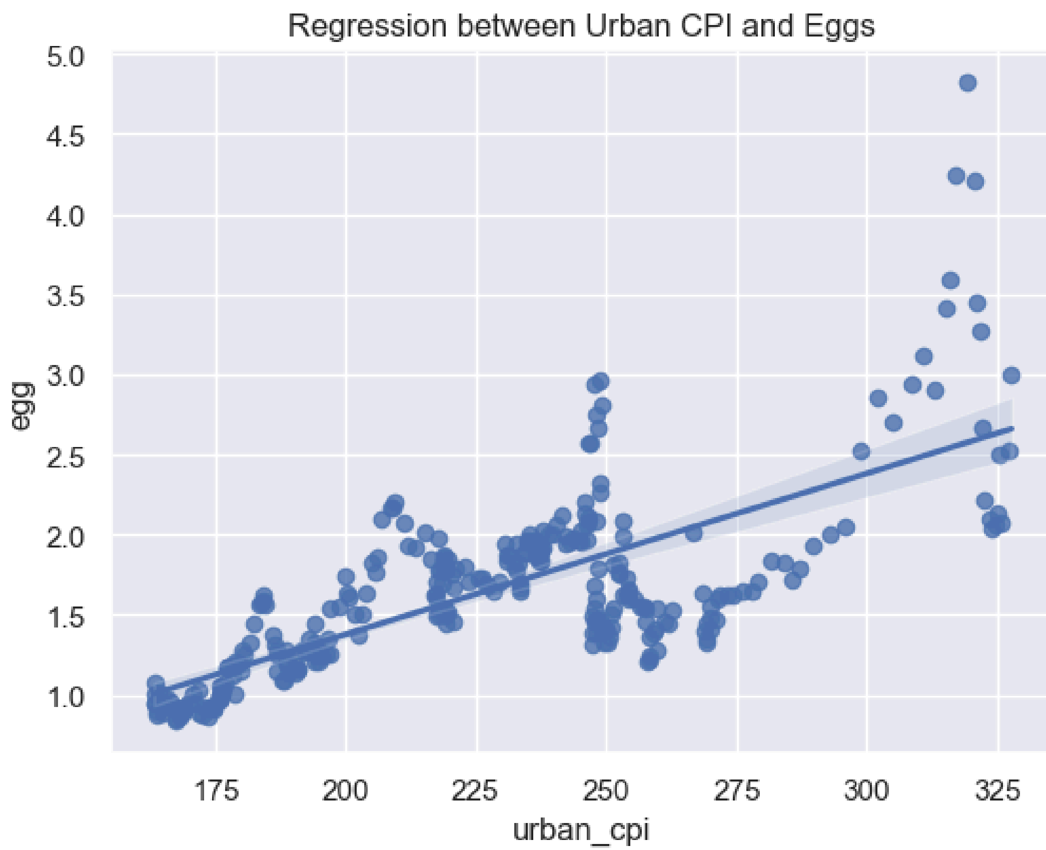
In [21]:
```
lr_preds_egg.axes
```

Out[21]:
```
[Index([223, 150, 226, 296,  52, 261, 246, 166, 221, 215, 225, 133, 214,  12,
         15,  66, 285,  89, 176, 101,  22, 205, 224, 212, 190, 129, 175, 136,
        152,  55, 201, 253, 144,   8, 271, 111, 263,  81, 184, 282,   5,  59,
        234, 241,  34, 250, 182, 122, 254,   7,  45, 216, 238,  63, 108, 118,
        137, 227,  26, 106,  92],
       dtype='int64')]
```

In [22]:
```
plt.scatter(lr_preds_egg.axes, lr_preds_egg)
# plt.title("Regression between Urban CPI and Eggs")
plt.show()
```



In [23]:
```
sns.regplot(x='urban_cpi', y='egg', data=groceries_df)
plt.title("Regression between Urban CPI and Eggs")
plt.show()
```



In [ ]:
```

```

In [ ]:
```

```

In [24]:
```
lr_model_milk = smf.ols(formula="urban_cpi ~ whole_milk", data=X_train).fit()
lr_model_milk.summary()
```

Out[24]:

OLS Regression Results

Dep. Variable:	urban_cpi	**R-squared:**	0.524
Model:	OLS	**Adj. R-squared:**	0.522
Method:	Least Squares	**F-statistic:**	262.1
Date:	Tue, 30 Apr 2024	**Prob (F-statistic):**	3.00e-40
Time:	10:34:50	**Log-Likelihood:**	-1154.1
No. Observations:	240	**AIC:**	2312.
Df Residuals:	238	**BIC:**	2319.
Df Model:	1		
Covariance Type:	nonrobust		

	coef	**std err**	**t**	**P>|t|**	**[0.025**	**0.975]**
Intercept	-30.8142	16.054	-1.919	0.056	-62.441	0.813
whole_milk	78.3447	4.839	16.189	0.000	68.811	87.878

Omnibus:	4.496	**Durbin-Watson:**	2.101
Prob(Omnibus):	0.106	**Jarque-Bera (JB):**	3.461
Skew:	0.172	**Prob(JB):**	0.177
Kurtosis:	2.523	**Cond. No.**	30.2

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

In [25]:
```
lr_preds_milk = lr_model_milk.predict(X_test)
lr_preds_milk
```

Out[25]:
```
223    220.593818
150    260.079533
226    216.363206
296    276.845293
52     178.836108
          ...
137    228.741664
227    201.164339
26     192.076357
106    272.379647
92     209.233841
Length: 61, dtype: float64
```

In [26]:
```
lr_model_milk.fittedvalues
```

Out[26]:
```
74     221.847333
239    197.403795
64     249.189624
294    276.845293
286    299.095180
          ...
251    224.040984
192    243.078739
117    261.724771
47     179.619554
172    240.101642
Length: 240, dtype: float64
```

In [27]:
```
sns.regplot(x='urban_cpi', y='whole_milk', data=groceries_df)
plt.title("Regression between Urban CPI and Whole Milk")
plt.show()
```

In [28]:
```python
# Single LR model between Urban CPI and Banana price
lr_model_banana = smf.ols(formula="urban_cpi ~ banana", data=X_train).fit()
lr_model_banana.summary()
```

Out[28]:

OLS Regression Results

Dep. Variable:	urban_cpi	**R-squared:**	0.648
Model:	OLS	**Adj. R-squared:**	0.646
Method:	Least Squares	**F-statistic:**	437.9
Date:	Tue, 30 Apr 2024	**Prob (F-statistic):**	7.36e-56
Time:	10:34:51	**Log-Likelihood:**	-1118.0
No. Observations:	240	**AIC:**	2240.
Df Residuals:	238	**BIC:**	2247.
Df Model:	1		
Covariance Type:	nonrobust		

	coef	**std err**	**t**	**P>|t|**	**[0.025**	**0.975]**
Intercept	-158.8139	18.523	-8.574	0.000	-195.303	-122.325
banana	686.1932	32.793	20.925	0.000	621.591	750.795

Omnibus:	1.096	**Durbin-Watson:**	1.960
Prob(Omnibus):	0.578	**Jarque-Bera (JB):**	1.202
Skew:	-0.130	**Prob(JB):**	0.548
Kurtosis:	2.771	**Cond. No.**	26.1

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

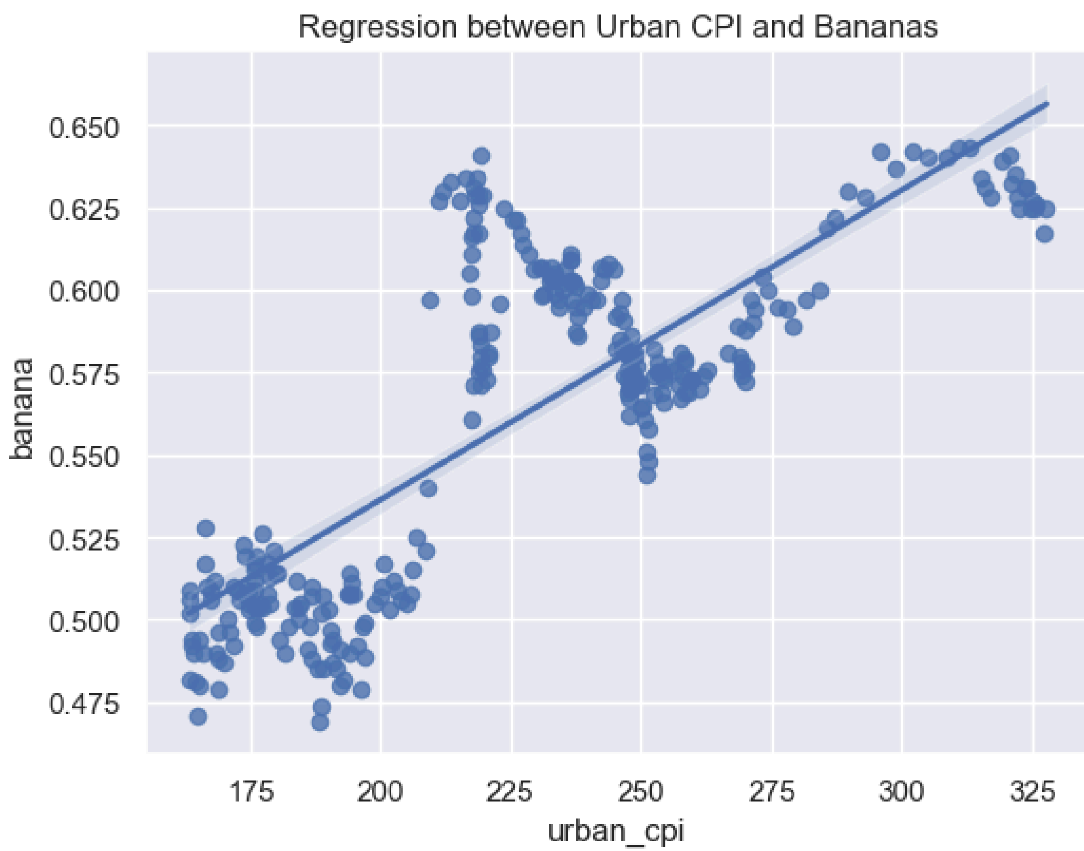
In [29]:
```python
lr_preds_banana = lr_model_banana.predict(X_test)
lr_preds_banana
```

Out[29]:
```
223    214.475165
150    257.019143
226    224.081870
296    270.743006
52     198.692722
          ...
137    241.236699
227    230.943801
26     178.793119
106    201.437494
92     176.734539
Length: 61, dtype: float64
```

In [30]:
```
lr_model_banana.fittedvalues
```

Out[30]:
```
74     186.341244
239    236.433347
64     182.910278
294    274.173972
286    272.115393
          ...
251    232.316188
192    246.726245
117    270.743006
47     202.123687
172    254.960563
Length: 240, dtype: float64
```

In [31]:
```
sns.regplot(x='urban_cpi', y='banana', data=groceries_df)
plt.title("Regression between Urban CPI and Bananas")
plt.show()
```



In [ ]:
```
 
```

In [ ]:
```
 
```

In [ ]:
```
 
```

In [ ]:
```
 
```

Multiple Linear Regression

To do multiple linear regression on more than one attribute of `groceries_df` , I will pick out specific columns of what is being listed as the independent variable and which columns are considered dependent variables.

I will continue to use `smf.ols` to fit the data and predict.

The columns that are to be used under X: month_number, white_bread, whole_milk, egg The column(s) under y: urban_cpi

Implement a multilinear regression model on four of the five items and fit the data to the `X_train` dataset.

In [32]:

```
# Four grocery items compared: white bread, whole milk, egg, ground beef to be fi
lr_model_multi_four = smf.ols('urban_cpi ~ white_bread \
                              + whole_milk + egg + \
                              ground_beef', data=X_train).fit()
lr_model_multi_four.summary()
```

Out[32]:

OLS Regression Results

Dep. Variable:	urban_cpi	**R-squared:**	0.966
Model:	OLS	**Adj. R-squared:**	0.966
Method:	Least Squares	**F-statistic:**	1693.
Date:	Tue, 30 Apr 2024	**Prob (F-statistic):**	6.51e-172
Time:	10:34:52	**Log-Likelihood:**	-835.81
No. Observations:	240	**AIC:**	1682.
Df Residuals:	235	**BIC:**	1699.
Df Model:	4		
Covariance Type:	nonrobust		

	coef	**std err**	**t**	**P>|t|**	**[0.025**	**0.975]**
Intercept	69.8511	5.213	13.399	0.000	59.580	80.122
white_bread	87.6140	4.814	18.199	0.000	78.130	97.098
whole_milk	-5.4505	2.341	-2.328	0.021	-10.063	-0.838
egg	-1.1216	1.517	-0.739	0.460	-4.111	1.867
ground_beef	21.1033	0.861	24.515	0.000	19.407	22.799

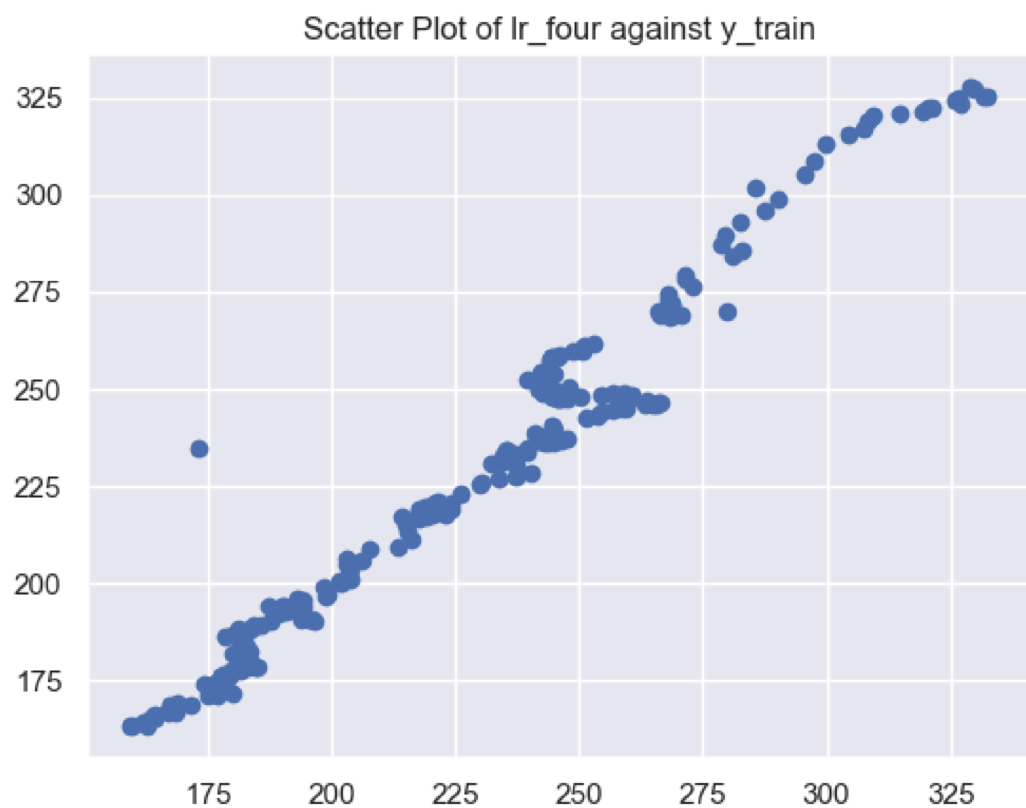
Omnibus:	137.270	**Durbin-Watson:**	2.259
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	2311.190
Skew:	1.841	**Prob(JB):**	0.00
Kurtosis:	17.750	**Cond. No.**	56.2

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

In [33]:
```
# Predict the CPI values (four items)
lr_four = lr_model_multi_four.predict(X_train)
lr_four
```

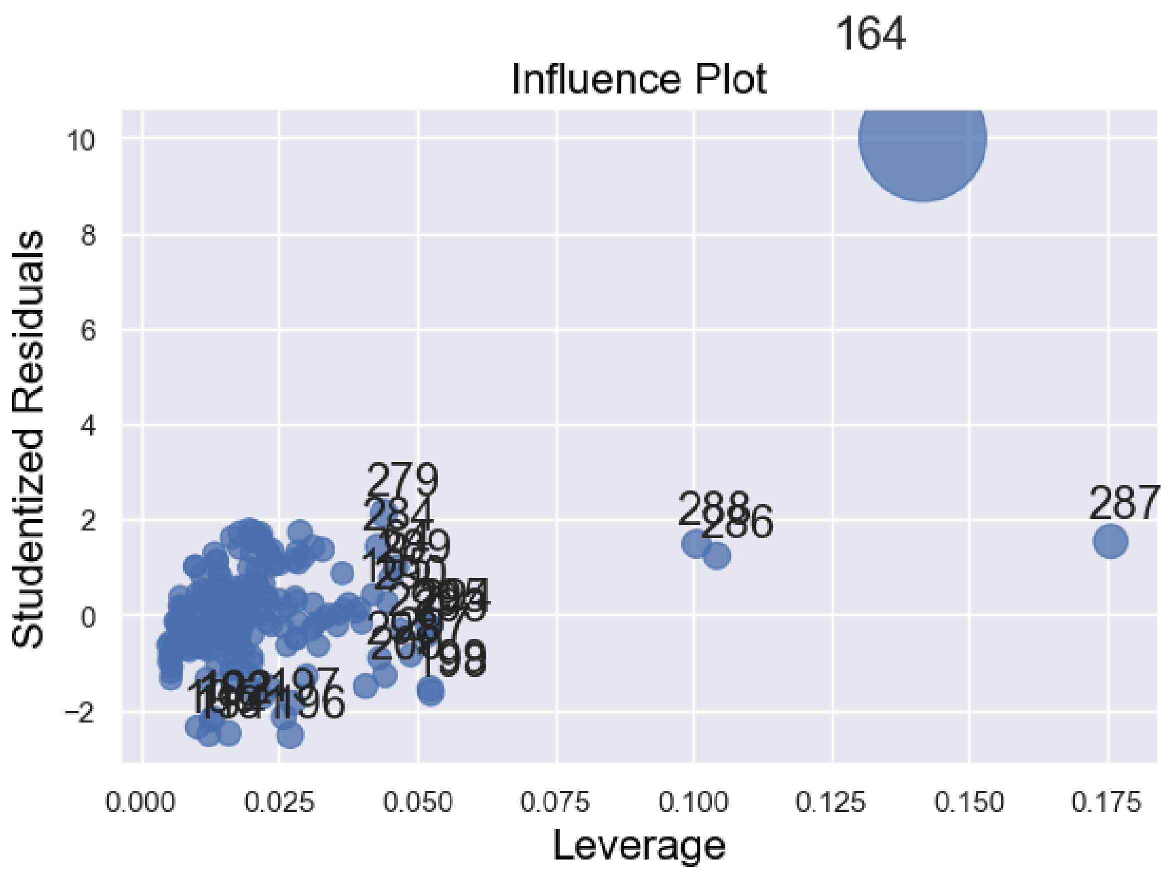
Out[33]:
```
74     187.659707
239    244.064792
64     178.527382
294    325.875595
286    307.529190
          ...
251    250.855988
192    263.616216
117    217.822411
47     181.526868
172    246.366184
Length: 240, dtype: float64
```

In [62]:
```
# Scatter plot of predicted results against actual CPI values

plt.scatter(lr_four, y_train)
plt.title("Scatter Plot of lr_four against y_train")
plt.show()
```



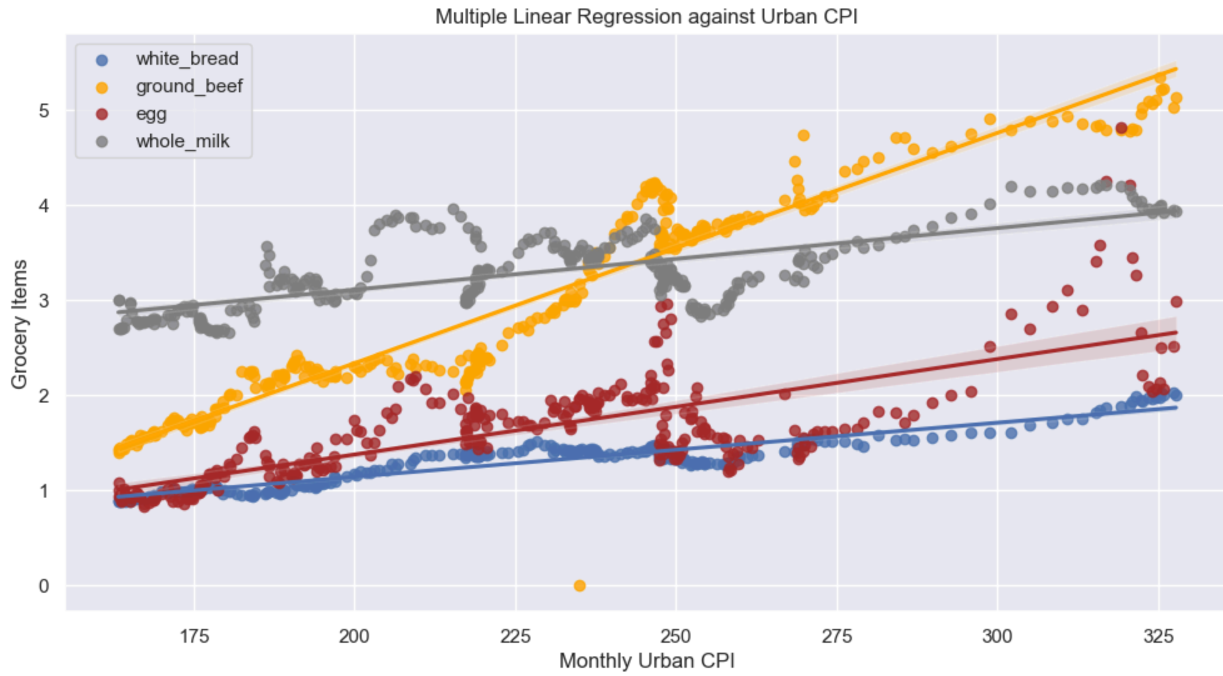
In [36]:

```
# Influence plot on the four items

fig = sm.graphics.influence_plot(lr_model_multi_four)
fig.tight_layout(pad=1.0)
plt.show()
```



In [63]:

```
# Four Grocery Items' Regression Plots

plt.figure(figsize=(12,6))
sns.regplot(x='urban_cpi', y='white_bread', data=groceries_df, label='white_bread
sns.regplot(x='urban_cpi', y='ground_beef', data=groceries_df, label='ground_beef
sns.regplot(x='urban_cpi', y='egg', data=groceries_df, label='egg', color='brown'
sns.regplot(x='urban_cpi', y='whole_milk', data=groceries_df, label='whole_milk',

plt.title("Multiple Linear Regression against Urban CPI")
plt.xlabel("Monthly Urban CPI")
plt.ylabel("Grocery Items")
plt.legend()
plt.show()
```



In [64]:

```
# All five grocery items compared: white bread, whole milk, egg, ground beef, bana

lr_model_multi_five = smf.ols('urban_cpi ~ white_bread \
                              + whole_milk + egg + \
                              ground_beef', data=X_train).fit()
lr_model_multi_five.summary()
```

Out[64]:

OLS Regression Results

Dep. Variable:	urban_cpi	**R-squared:**	0.966
Model:	OLS	**Adj. R-squared:**	0.966
Method:	Least Squares	**F-statistic:**	1693.
Date:	Tue, 30 Apr 2024	**Prob (F-statistic):**	6.51e-172
Time:	10:52:05	**Log-Likelihood:**	-835.81
No. Observations:	240	**AIC:**	1682.
Df Residuals:	235	**BIC:**	1699.
Df Model:	4		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
Intercept	69.8511	5.213	13.399	0.000	59.580	80.122
white_bread	87.6140	4.814	18.199	0.000	78.130	97.098
whole_milk	-5.4505	2.341	-2.328	0.021	-10.063	-0.838
egg	-1.1216	1.517	-0.739	0.460	-4.111	1.867
ground_beef	21.1033	0.861	24.515	0.000	19.407	22.799

Omnibus:	137.270	**Durbin-Watson:**	2.259
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	2311.190
Skew:	1.841	**Prob(JB):**	0.00
Kurtosis:	17.750	**Cond. No.**	56.2

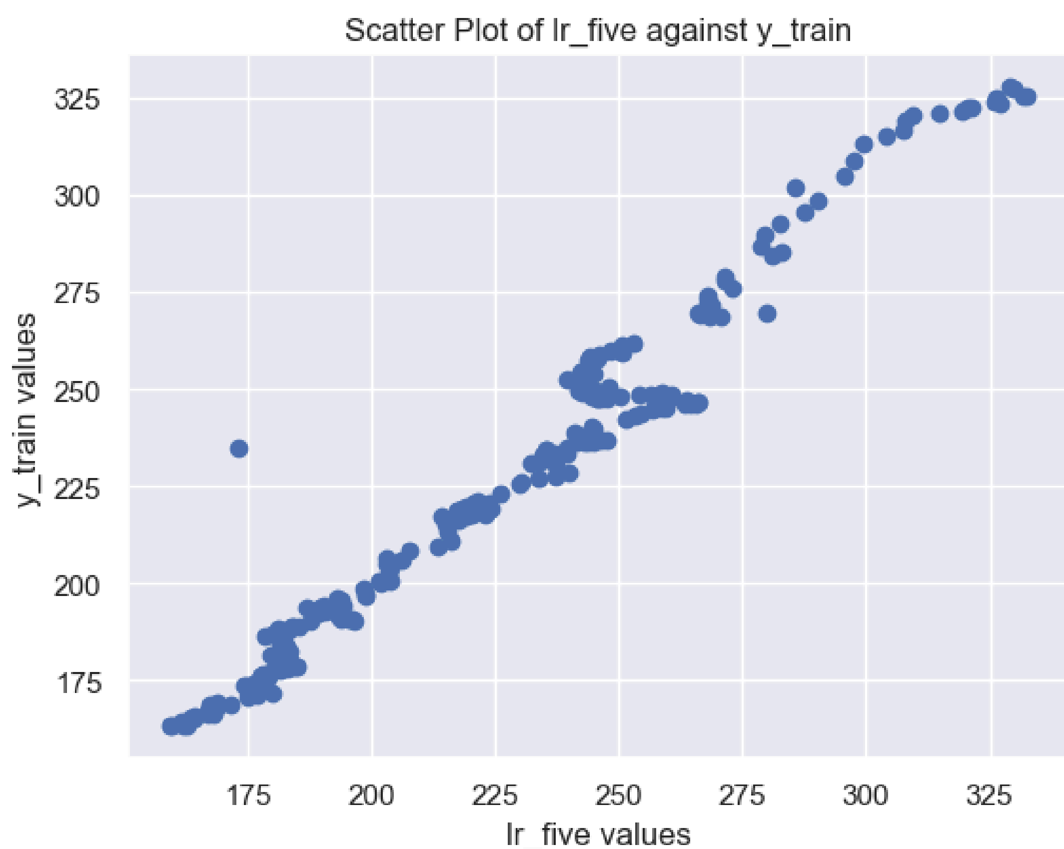
Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.

In [61]:
```python
# Predict the CPI values (four items)

lr_five = lr_model_multi_five.predict(X_train)
lr_five
```

Out[61]:
```
74     187.659707
239    244.064792
64     178.527382
294    325.875595
286    307.529190
          ...
251    250.855988
192    263.616216
117    217.822411
47     181.526868
172    246.366184
Length: 240, dtype: float64
```

In [65]:
```python
# Scatter plot of predicted results on the five items against actual CPI values

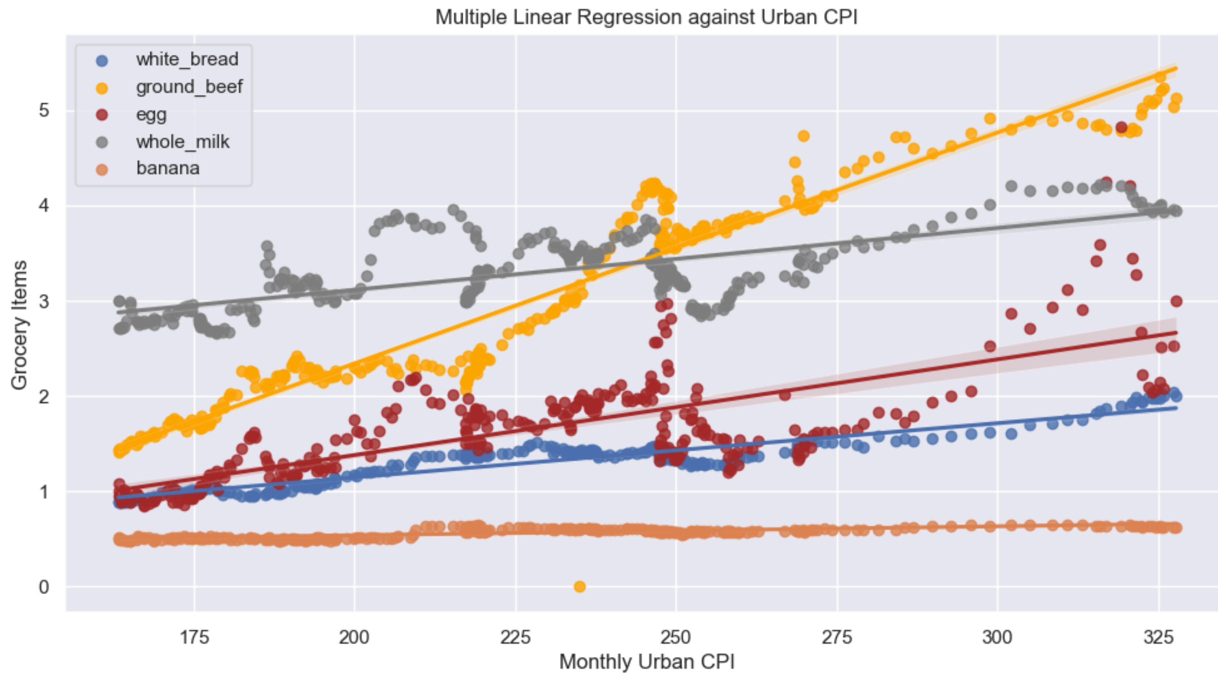
plt.scatter(lr_five, y_train)
plt.title("Scatter Plot of lr_five against y_train")
plt.xlabel("lr_five values")
plt.ylabel("y_train values")
plt.show()
```



In [59]:
```
# Five Grocery Items' Regression Plots

plt.figure(figsize=(12,6))
sns.regplot(x='urban_cpi', y='white_bread', data=groceries_df, label='white_bread
sns.regplot(x='urban_cpi', y='ground_beef', data=groceries_df, label='ground_beef
sns.regplot(x='urban_cpi', y='egg', data=groceries_df, label='egg', color='brown'
sns.regplot(x='urban_cpi', y='whole_milk', data=groceries_df, label='whole_milk',
sns.regplot(x='urban_cpi', y='banana', data=groceries_df, label='banana')

plt.title("Multiple Linear Regression against Urban CPI")
plt.xlabel("Monthly Urban CPI")
plt.ylabel("Grocery Items")
plt.legend()
plt.show()
```



In [ ]:
```

```

We can see that based on the R-squared value that there is a positive relationship between the Urban CPI and any combination of four of the five grocery items. In this case, I compared the Urban CPI to the sum of the coefficients of white bread, whole milk, eggs, and ground beef.

In [ ]:
```

```

In [37]:
```
# Just using two grocery items for comparison: whole milk and egg

lr_model_multi_two = smf.ols('urban_cpi ~ whole_milk + egg', data=X_train).fit()
lr_model_multi_two.summary()
```

Out[37]:

OLS Regression Results

Dep. Variable:	urban_cpi	**R-squared:**	0.610
Model:	OLS	**Adj. R-squared:**	0.607
Method:	Least Squares	**F-statistic:**	185.2
Date:	Tue, 30 Apr 2024	**Prob (F-statistic):**	3.70e-49
Time:	10:34:55	**Log-Likelihood:**	-1130.3
No. Observations:	240	**AIC:**	2267.
Df Residuals:	237	**BIC:**	2277.
Df Model:	2		
Covariance Type:	nonrobust		

	coef	**std err**	**t**	**P>|t|**	**[0.025**	**0.975]**
Intercept	38.5488	17.454	2.209	0.028	4.164	72.933
whole_milk	40.7878	6.810	5.989	0.000	27.372	54.204
egg	32.7281	4.536	7.215	0.000	23.792	41.664

Omnibus:	15.872	**Durbin-Watson:**	2.124
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	15.616
Skew:	0.574	**Prob(JB):**	0.000406
Kurtosis:	2.505	**Cond. No.**	41.7

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

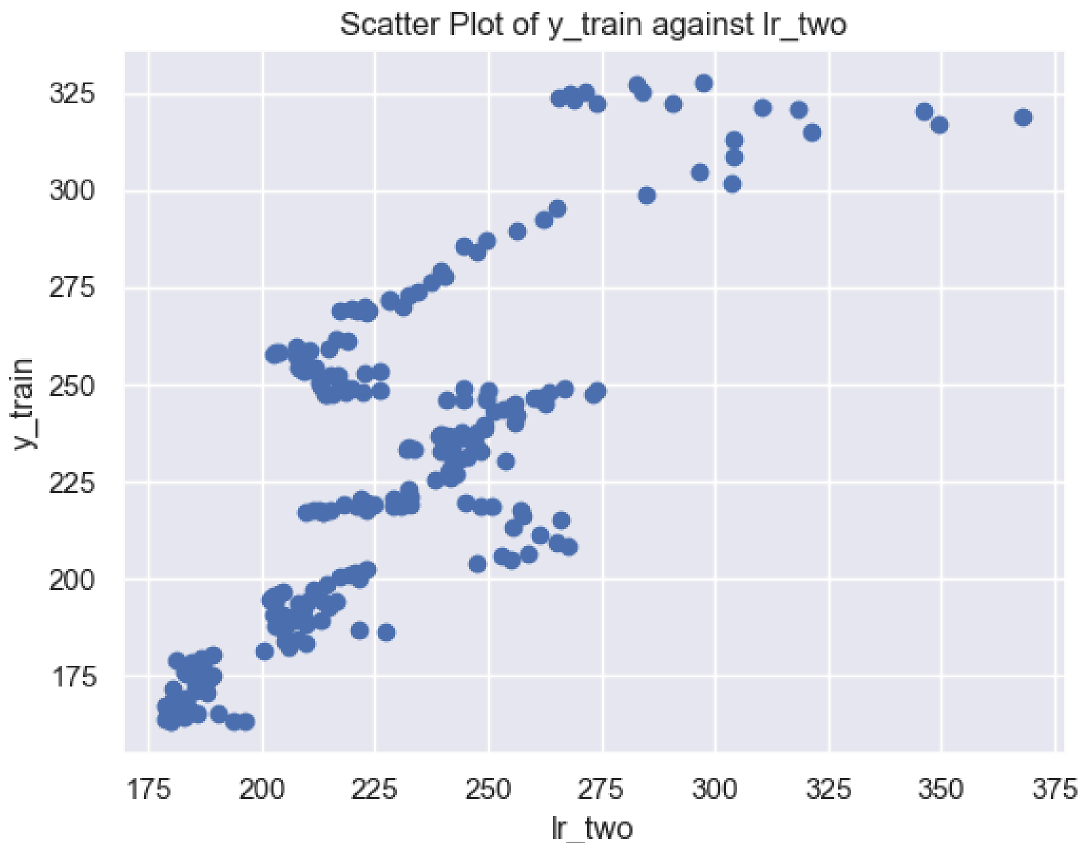
In [38]:
```
lr_two = lr_model_multi_two.predict(X_train)
lr_two
```

Out[38]:
```
74     208.185030
239    208.223163
64     227.231012
294    265.586057
286    349.400619
          ...
251    219.047322
192    249.479258
117    251.004752
47     186.560390
172    240.434595
Length: 240, dtype: float64
```

In [67]:

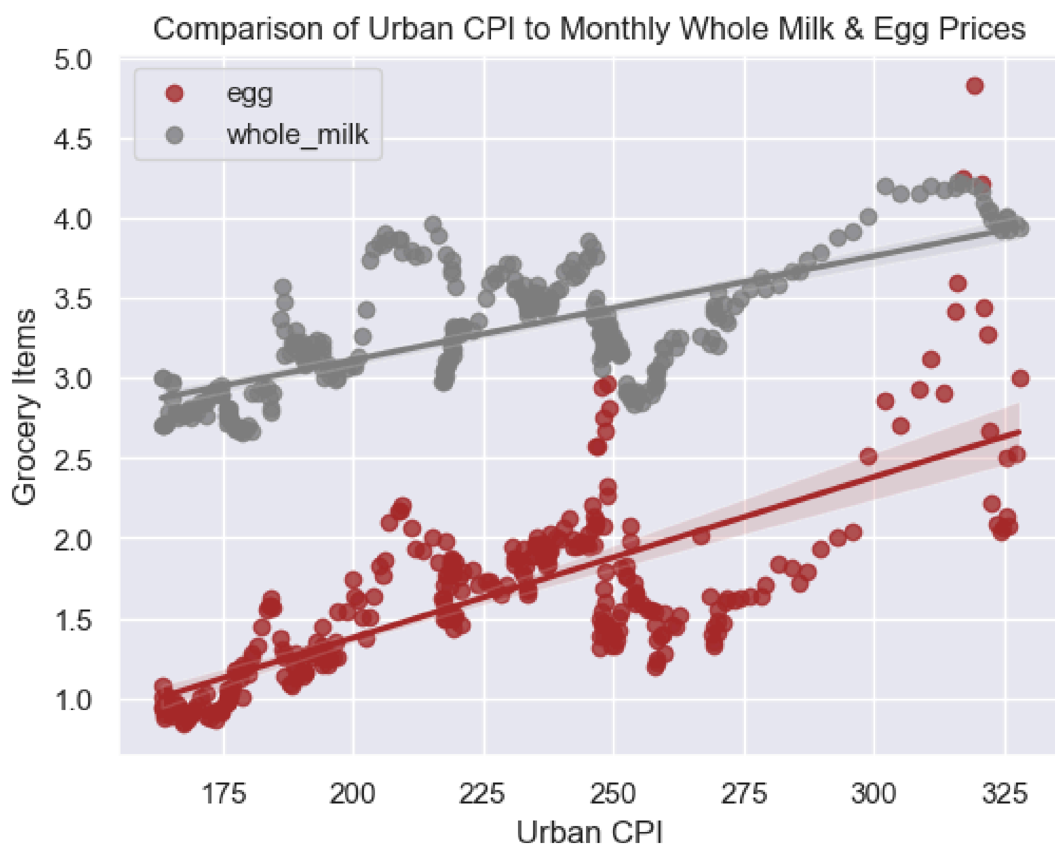
```
# Note how the scatter plot for two items is different from those of four and five
# The regression line would be off

plt.scatter(lr_two, y_train)
plt.title("Scatter Plot of y_train against lr_two")
plt.xlabel("lr_two")
plt.ylabel("y_train")
plt.show()
```

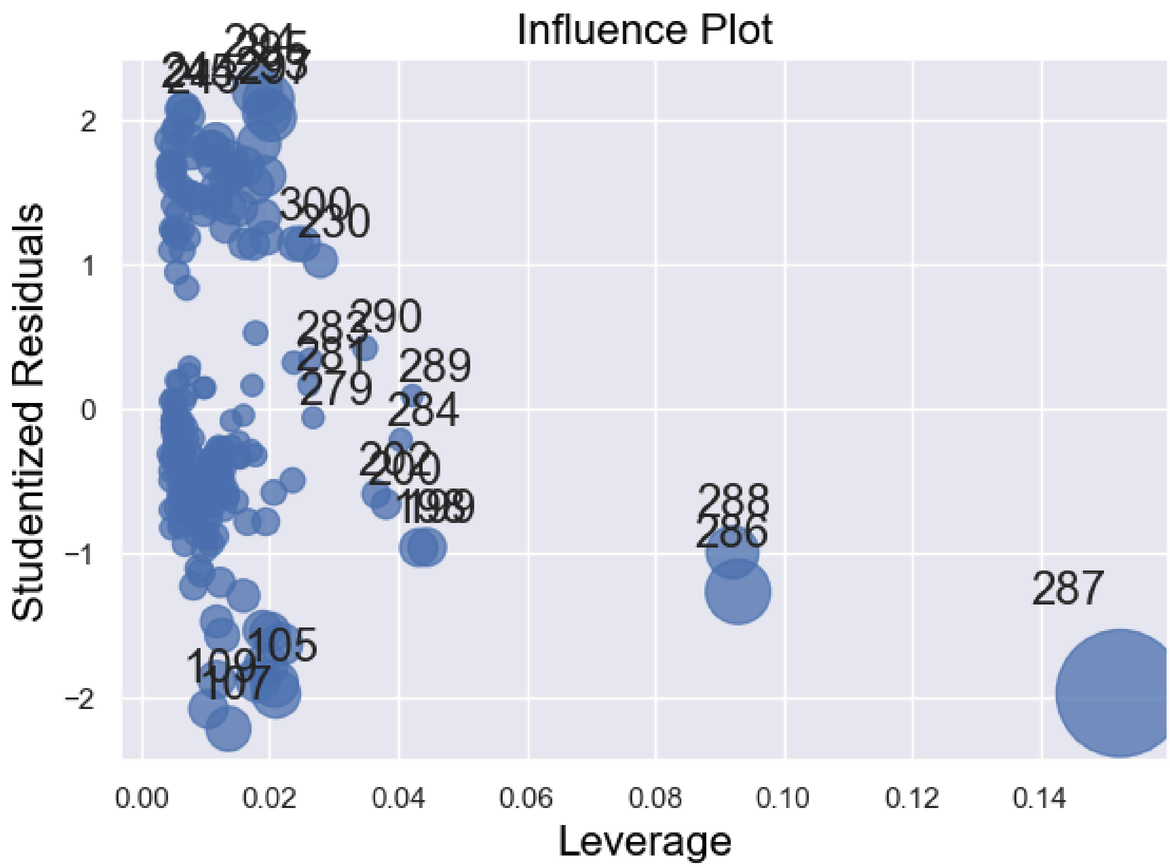


In [68]:

```
# Regression plots of egg and whole milk
sns.regplot(x='urban_cpi', y='egg', data=groceries_df, label='egg', color='brown'
sns.regplot(x='urban_cpi', y='whole_milk', data=groceries_df, label='whole_milk',
plt.ylabel("Grocery Items")
plt.xlabel("Urban CPI")
plt.title("Comparison of Urban CPI to Monthly Whole Milk & Egg Prices")
plt.legend()
plt.show()
```



In [41]:
```
fig = sm.graphics.influence_plot(lr_model_multi_two)
fig.tight_layout(pad=1.0)
plt.show()
```



In [ ]:
```

```

In [ ]:
```

```

Conclusion

We can see that all of the five grocery items picked for this evaluation have had their average prices increased over the 25-year period. Each of the five individual grocery items, when compared to the monthly urban CPI, had some form of correlation to the urban CPI. Of the five, however, the item which had data points that were closest to the regression coefficients was ground beef, where the monthly average price by the pound was nearly steady with the rise in the CPI.

The comparison of two different kinds of linear regression models from two different Python libraries, with two different methods of conducting this form of supervised learning. The statsmodels version provided immediate fitting and prediction value sets that could easily be presented visually, and provides entire arrays worth of predicted values with respect to the urban CPI.

It can be seen that the fewer items are involved in prediction models, the less likely that one item will have a strong connection with the CPI. If all five items are included, the connection is higher. Both single and multiple linear regression show that this will be the case with the prices of items gradually rising despite periods of faster price hikes.

These five grocery items alone only portray just a small picture of how it can be affected by the overall urban CPI, and the CPI itself. The overall cost of groceries have gone up over time, independent of other external factors (public health crises, climate change, rapid economic change, etc.). Even looking at just the average monthly prices at face value, without the analysis, prices have been and will continue to go up. Supply and demand might be one of the key causes of the increase in costs and spending, but how tightly related produce, meats, or grains, among other agricultural fields, are to CPI here in the US and around the world, will depend on other factors in how consumers purchase what food they need.

The price of items as well as the CPI in the US will rise gradually and not accelerate as initially thought. Despite challenges with being able to explicitly outline the constant rise, there will be no faster growth. When prices of grocery items drop or remain the same on a monthly basis, the mean price growth will slow down and the slope be closer to zero. Barring external factors and the types of items, growth of the CPI will likely continue to increase while the rate of the prices of items purchased will increase at slower,

In [ ]:
```
1
```

References

FRED, Federal Reserve Bank of St. Louis. (n.d.). *Average Price: Bananas (Cost per Pound/453.6Grams) in U.S. City Average [APU0000711211]*. [Unpublished raw data]. Retrieved April 3, 2024, from https://fred.stlouisfed.org/series/APU0000711211.

FRED, Federal Reserve Bank of St. Louis. (n.d.). *Average Price: Bread, White, Pan (Cost perPound/453.6 Grams) in U.S. City Average [APU0000702111]*. [Unpublished raw data]. Retrieved April 2, 2024, from [https://fred.stlouisfed.org/series/APU0000702111 (https://fred.stlouisfed.org/series/APU0000702111)](https://fred.stlouisfed.org/series/APU0000702111).

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FRED, Federal Reserve Bank of St. Louis. (n.d.). *Average Price: Ground Beef, 100% Beef (Cost perPound/453.6 Grams) in U.S. City Average [APU0000703112]*. [Unpublished raw data]. Retrieved April 8, 2024, from [https://fred.stlouisfed.org/series/APU0000703112 (https://fred.stlouisfed.org/series/APU0000703112)](https://fred.stlouisfed.org/series/APU0000703112).

FRED, Federal Reserve Bank of St. Louis. (n.d.). *Consumer Price Index for All Urban Consumers: Foodin U.S. City Average [CPIUFDNS]*. [Unpublished raw data]. Retrieved March 31, 2024, from [https://fred.stlouisfed.org/series/CPIUFDNS (https://fred.stlouisfed.org/series/CPIUFDNS)](https://fred.stlouisfed.org/series/CPIUFDNS).

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In [ ]:
```
1
```

In [ ]:
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1
```