Linear & Ridge Regression Analysis

Data and Libraries

In [3]:
```
# Import libraries
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LinearRegression
from sklearn.metrics import mean_absolute_error, mean_squared_error, r2_score
from sklearn.preprocessing import StandardScaler
from sklearn.linear_model import Ridge
from statsmodels.stats.outliers_influence import variance_inflation_factor
from sklearn.model_selection import GridSearchCV
```

In [4]:
```
# Import historical almond pricing and production data
almond_df = pd.read_excel('AlmondData.xlsx')

# Import historical US population data
uspopulation_df = pd.read_excel('USPopulation.xlsx')

# Import historical USD Index data
usindex_df = pd.read_excel('USDollarIndex.xlsx')
```

Data Preparation

In [6]:
```
# Merge US population data into almond data frame
almond_df['USPopulation_Millions'] = uspopulation_df['July 1 (million people)1']
```

In [7]:
```
# Filter US Index data from 1981 to 2024
usindex_1981to2024 = usindex_df.loc[usindex_df['Year (last business day)'] >= 1981, :]

# Reset index
usindex_1981to2024 = usindex_1981to2024.reset_index()
```

In [8]:
```
# Merge USDIndex data into almond data frame
almond_df['USDIndex'] = usindex_1981to2024['DXY close']
```

In [9]:
```
# Save marketing years
marketing_year = almond_df['Marketing_Year']
```

In [10]:
```
# Drop unnecessary columns
uncolumns = ['Marketing_Year','Yield_Lbs_Per_Acre',
             'Value_of_Production_Usd_Mill','Utilized_Production_Lbs_Mill',
             'Current_Reserve_Lbs_Mill','Percapita_Availability_Lbs']

# Drop columns
almond_df.drop(columns=uncolumns, inplace=True)
```

In [11]:
```python
# Show final data frame
almond_df.head()
```

Out[11]:

	Bearing_Acres_Th	Total_Production_Lbs_Mill	Price_Cents_Per_Lb	Loss_Production_Lbs_Mill	Marketable_P
0	326.8	322	147.0	16.86	
1	326.2	408	78.0	24.87	
2	339.0	347	94.0	16.24	
3	360.0	242	104.0	20.21	
4	381.0	590	77.4	26.36	

Linear Regression Analysis

In [13]:
```python
# Create X feature matrix
X = almond_df.drop(columns='Price_Cents_Per_Lb')

# Select target variable
y = almond_df['Price_Cents_Per_Lb']
```

In [14]:
```python
# Split data into training and testing sets (80%/20%)
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.20, random_state=42)
```

In [15]:
```python
# Create model
model = LinearRegression()

# Fit model
model.fit(X_train, y_train)
```

Out[15]:
```
▾ LinearRegression
LinearRegression()
```

In [16]:
```python
# Test model
y_pred = model.predict(X_test)
```

In [17]:
```python
# Calculate error metrics
mae = mean_absolute_error(y_test, y_pred)
mse = mean_squared_error(y_test, y_pred)
rmse = np.sqrt(mse)
r2 = r2_score(y_test, y_pred)

# Print evaluation metrics
print(f"Mean Absolute Error (MAE): {mae:.2f}")
print(f"Mean Squared Error (MSE): {mse:.2f}")
print(f"Root Mean Squared Error (RMSE): {rmse:.2f}")
print(f"R² Score: {r2:.4f}")
```

```
Mean Absolute Error (MAE): 32.71
Mean Squared Error (MSE): 2473.63
Root Mean Squared Error (RMSE): 49.74
R² Score: 0.7233
```

In [18]:
```python
# Get the feature importance (coefficients)
coefficients = pd.DataFrame({'Feature': X.columns, 'Coefficient': model.coef_})

# Print coefficients
print(coefficients.sort_values(by='Coefficient', ascending=False))
```

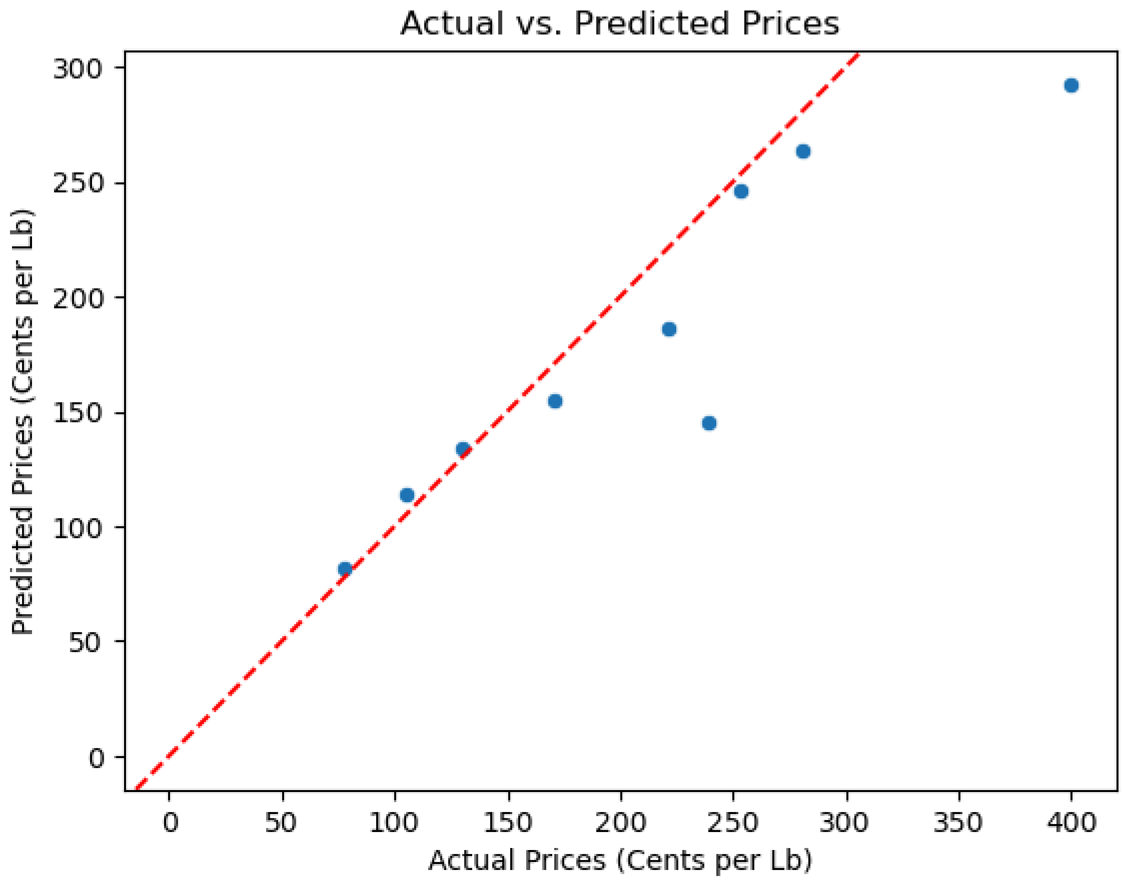
```
                          Feature  Coefficient
4                Imports_lbs_Mill     3.967334
6                 Supply_Lbs_Mill     2.122925
8                Exports_Lbs_Mill     0.846494
7          Ending_Stocks_Lbs_Mill     0.774407
10          USPopulation_Millions     0.728366
2        Loss_Production_Lbs_Mill     0.675250
9   Domestic_Availability_Lbs_Mill     0.502024
0                Bearing_Acres_Th     0.279754
5       Beginning_Stocks_Lbs_Mill    -0.003078
11                       USDIndex    -1.023544
1       Total_Production_Lbs_Mill    -1.169156
3   Marketable_Production_Lbs_Mill    -1.844406
```

In [19]:
```python
# Plot scatter plot
sns.scatterplot(x=y_test, y=y_pred)

# Show ideal line
plt.axline([0, 0], [1, 1], color="red", linestyle="--")

# Plot labels
plt.xlabel("Actual Prices (Cents per Lb)")
plt.ylabel("Predicted Prices (Cents per Lb)")
plt.title("Actual vs. Predicted Prices")

# Show chart
plt.show()
```



Ridge Regression Analysis

In [21]:
```
# Create empty data frame
vif_data = pd.DataFrame()

# Add feature matrix as columns
vif_data["Feature"] = X.columns

# Compute the Variance Inflation Factor (VIF) for each feature
vif_data["VIF"] = [variance_inflation_factor(X.values, i) for i in range(len(X.columns))]

# Show VIF
print(vif_data)
```

```
                        Feature          VIF
0               Bearing_Acres_Th   353.929946
1         Total_Production_Lbs_Mill          inf
2          Loss_Production_Lbs_Mill          inf
3   Marketable_Production_Lbs_Mill          inf
4               Imports_lbs_Mill    23.959837
5         Beginning_Stocks_Lbs_Mill  6262.688105
6                Supply_Lbs_Mill          inf
7            Ending_Stocks_Lbs_Mill          inf
8               Exports_Lbs_Mill          inf
9   Domestic_Availability_Lbs_Mill          inf
10            USPopulation_Millions    78.593529
11                       USDIndex    50.163597
```

```
C:\Users\emili\anaconda3\Lib\site-packages\statsmodels\stats\outliers_influence.py:198: RuntimeWa
rning: divide by zero encountered in scalar divide
  vif = 1. / (1. - r_squared_i)
```

In [22]:
```
# Create standard scaler
scaler = StandardScaler()

# Fit scaler
X_train_scaled = scaler.fit_transform(X_train)

# Transfrom test matrix
X_test_scaled = scaler.transform(X_test)
```

In [23]:
```
# Initialize Ridge regression
ridge_model = Ridge(alpha=1.0)

# Fit training data into model
ridge_model.fit(X_train_scaled, y_train)

# Make predictions
y_pred = ridge_model.predict(X_test_scaled)
```

In [24]:
```
# Calculate error metrics
mae = mean_absolute_error(y_test, y_pred)
mse = mean_squared_error(y_test, y_pred)
rmse = np.sqrt(mse)
r2 = r2_score(y_test, y_pred)

# Print evaluation metrics
print(f"Mean Absolute Error (MAE): {mae:.2f}")
print(f"Mean Squared Error (MSE): {mse:.2f}")
print(f"Root Mean Squared Error (RMSE): {rmse:.2f}")
print(f"R² Score: {r2:.4f}")
```

```
Mean Absolute Error (MAE): 31.10
Mean Squared Error (MSE): 2595.78
Root Mean Squared Error (RMSE): 50.95
R² Score: 0.7097
```

In [25]:
```
# Get the feature importance (coefficients)
coefficients = pd.DataFrame({'Feature': X.columns, 'Coefficient': ridge_model.coef_})

# Show coefficients
print(coefficients.sort_values(by='Coefficient', ascending=False))
```

```
                        Feature  Coefficient
4               Imports_lbs_Mill    63.297927
0               Bearing_Acres_Th    27.864404
10          USPopulation_Millions    20.523656
8               Exports_Lbs_Mill    -0.277304
2        Loss_Production_Lbs_Mill    -3.913615
5       Beginning_Stocks_Lbs_Mill    -6.271804
6                Supply_Lbs_Mill    -8.053045
1       Total_Production_Lbs_Mill    -9.090824
3   Marketable_Production_Lbs_Mill    -9.170580
7          Ending_Stocks_Lbs_Mill   -11.888543
11                      USDIndex   -14.186478
9   Domestic_Availability_Lbs_Mill   -22.994026
```

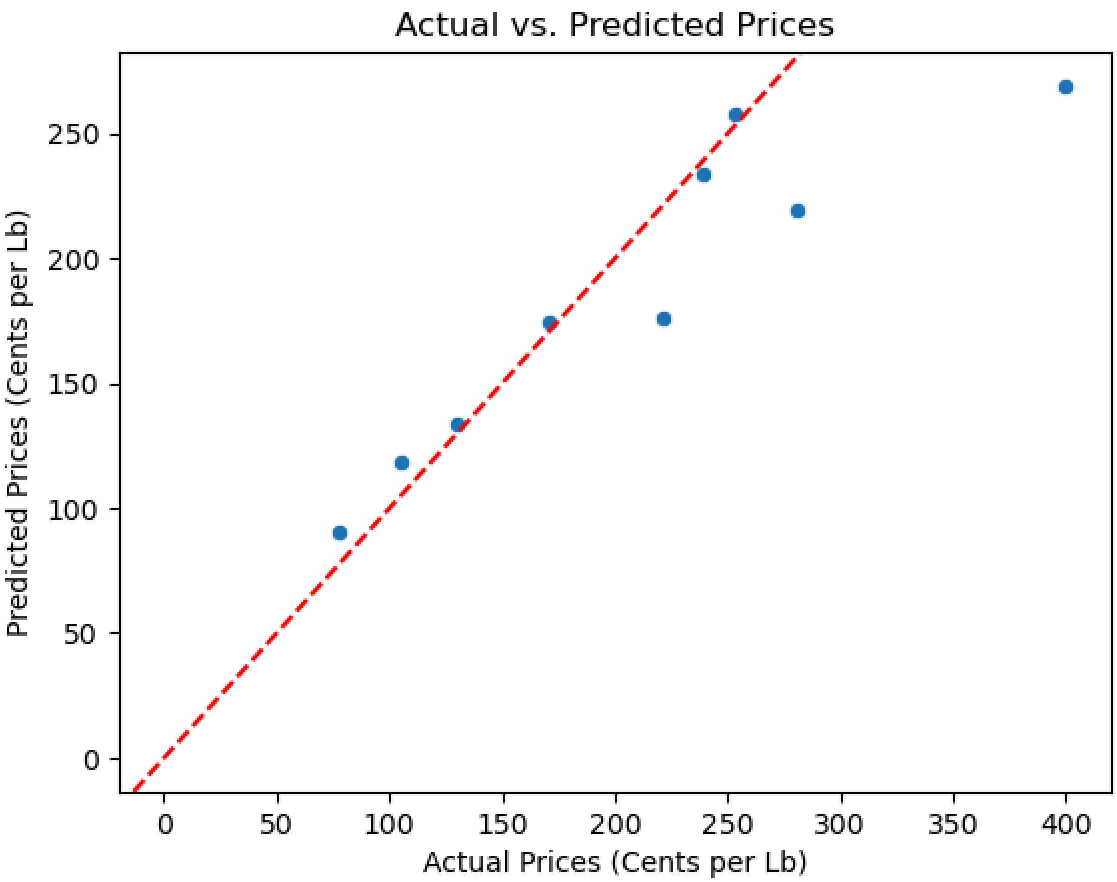
In [26]:
```
# Plot scatter plot
sns.scatterplot(x=y_test, y=y_pred)

# Show ideal line
```

```
plt.axline([0, 0], [1, 1], color="red", linestyle="--")

# Plot labels
plt.xlabel("Actual Prices (Cents per Lb)")
plt.ylabel("Predicted Prices (Cents per Lb)")
plt.title("Actual vs. Predicted Prices")

# Show chart
plt.show()
```



Ridge Model Optimization

In [28]:
```
# Define a range of alpha values
alphas = {'alpha': np.logspace(-3, 3, 10)}
```

In [29]:
```
# Create Grid Search model with Cross-Validation
ridge_cv = GridSearchCV(Ridge(), alphas, cv=5, scoring='r2')

# Fit Grid Search model
ridge_cv.fit(X_train_scaled, y_train)
```

Out[29]:

▸ **GridSearchCV**

▸ **estimator: Ridge**

▸ Ridge

In [30]:
```
# Get the best alpha
best_alpha = ridge_cv.best_params_['alpha']
```

```
# Print result
print(f"Best Alpha: {best_alpha}")
```

```
Best Alpha: 2.154434690031882
```

In [31]:
```
# Set Ridge model with optimized alpha value
ridge_model_optimal = Ridge(alpha=best_alpha)

# Fit training data into Ridge model
ridge_model_optimal.fit(X_train_scaled, y_train)
```

Out[31]:
```
▾ Ridge
Ridge(alpha=2.154434690031882)
```

In [32]:
```
# Make predictions with optimized Ridge model
y_pred_optimal = ridge_model_optimal.predict(X_test_scaled)
```

In [33]:
```
# Calculate error metrics
mae = mean_absolute_error(y_test, y_pred_optimal)
mse = mean_squared_error(y_test, y_pred_optimal)
rmse = np.sqrt(mse)
r2 = r2_score(y_test, y_pred_optimal)

# Print evaluation metrics
print(f"Optimized Mean Absolute Error (MAE): {mae:.2f}")
print(f"Optimized Mean Squared Error (MSE): {mse:.2f}")
print(f"Optimized Root Mean Squared Error (RMSE): {rmse:.2f}")
print(f"Optimized R² Score: {r2:.4f}")
```

```
Optimized Mean Absolute Error (MAE): 36.26
Optimized Mean Squared Error (MSE): 3233.40
Optimized Root Mean Squared Error (RMSE): 56.86
Optimized R² Score: 0.6383
```

In [34]:
```
# Get the feature importance (coefficients)
coefficients = pd.DataFrame({'Feature': X.columns, 'Coefficient': ridge_model_optimal.coef_})

# Show coefficients
print(coefficients.sort_values(by='Coefficient', ascending=False))
```

```
                        Feature  Coefficient
4               Imports_lbs_Mill    54.560576
10          USPopulation_Millions    16.154383
0               Bearing_Acres_Th    15.279725
8               Exports_Lbs_Mill    -0.141693
2        Loss_Production_Lbs_Mill    -3.505363
5       Beginning_Stocks_Lbs_Mill    -4.517457
6                Supply_Lbs_Mill    -4.977698
1       Total_Production_Lbs_Mill    -5.722350
3   Marketable_Production_Lbs_Mill    -5.751424
9   Domestic_Availability_Lbs_Mill    -9.885883
7          Ending_Stocks_Lbs_Mill   -12.762904
11                       USDIndex   -13.444154
```

In [35]:
```
# Plot optimized Ridge regression model
sns.scatterplot(x=y_test, y=y_pred_optimal)
```

```python
# Show ideal line
plt.axline([0, 0], [1, 1], color="red", linestyle="--")

# Plot labels
plt.xlabel("Actual Prices (Cents per Lb)")
plt.ylabel("Predicted Prices (Cents per Lb)")
plt.title("Optimized Ridge Model - Actual vs. Predicted Prices")

# Show chart
plt.show()
```