In [8]:
```
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
from statsmodels.tsa.arima.model import ARIMA
from statsmodels.tsa.statespace.sarimax import SARIMAX

# Load dataset
data = pd.read_csv('C:\Vidya\Masters\DSC680\Project2\Quarterly_Retail_Sales_Tax_Data_b

# Data Preprocessing
# Handle missing values
data.ffill(inplace=True)

# Convert infinite values to NaN
data.replace([np.inf, -np.inf], np.nan, inplace=True)

# Convert 'Quarter Ending' to datetime
data['Quarter Ending'] = pd.to_datetime(data['Quarter Ending'], errors='coerce')

# Drop rows with invalid dates
data.dropna(subset=['Quarter Ending'], inplace=True)

# Extract year and quarter from 'Quarter Ending'
data['Year'] = data['Quarter Ending'].dt.year
data['Quarter'] = data['Quarter Ending'].dt.quarter

# EDA
# Summary statistics
print(data.describe())

# Visualize data distributions
sns.histplot(data['Taxable Sales'].dropna(), kde=True)  # Drop NaN values for the plot
plt.title('Distribution of Taxable Sales')
plt.show()

# Aggregate sales and tax data by county and city
county_city_sales = data.groupby(['County', 'City'])['Taxable Sales'].sum().reset_inde
print(county_city_sales.head())

# Comparative Analysis
# Rank counties and cities based on their sales performance
county_city_sales['Rank'] = county_city_sales['Taxable Sales'].rank(ascending=False)
print(county_city_sales.sort_values('Rank').head())

# Feature Engineering
# Create new features
data['Sales Per Capita'] = data['Taxable Sales'] / data['Number of Returns']
data['Sales Growth Rate'] = data['Taxable Sales'].pct_change()

# Model Building
# Linear Regression
X = data[['Year', 'Quarter']]
y = data['Taxable Sales']
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=
```

```
lr_model = LinearRegression()
lr_model.fit(X_train, y_train)
y_pred_lr = lr_model.predict(X_test)

# Model Evaluation
mae_lr = mean_absolute_error(y_test, y_pred_lr)
mse_lr = mean_squared_error(y_test, y_pred_lr)
rmse_lr = np.sqrt(mse_lr)
print(f'Linear Regression MAE: {mae_lr}, MSE: {mse_lr}, RMSE: {rmse_lr}')

# ARIMA
arima_model = ARIMA(data['Taxable Sales'], order=(5, 1, 0))
arima_result = arima_model.fit()
arima_pred = arima_result.forecast(steps=len(y_test))
print(arima_result.summary())

# SARIMA
sarima_model = SARIMAX(data['Taxable Sales'], order=(1, 1, 1), seasonal_order=(1, 1, 1
sarima_result = sarima_model.fit()
sarima_pred = sarima_result.forecast(steps=len(y_test))
print(sarima_result.summary())

# Visualization
# Sales and tax contributions by county and city
plt.figure(figsize=(10, 6))
sns.barplot(x='County', y='Taxable Sales', data=county_city_sales.sort_values('Taxable
plt.title('Sales by County')
plt.xticks(rotation=90)
plt.show()

# Model predictions vs actual sales
plt.figure(figsize=(10, 6))
plt.plot(data['Fiscal Year'], data['Taxable Sales'], label='Actual Sales')
plt.plot(data['Fiscal Year'], lr_model.predict(X), label='Linear Regression Predictior
plt.legend()
plt.title('Model Predictions vs Actual Sales')
plt.show()
```

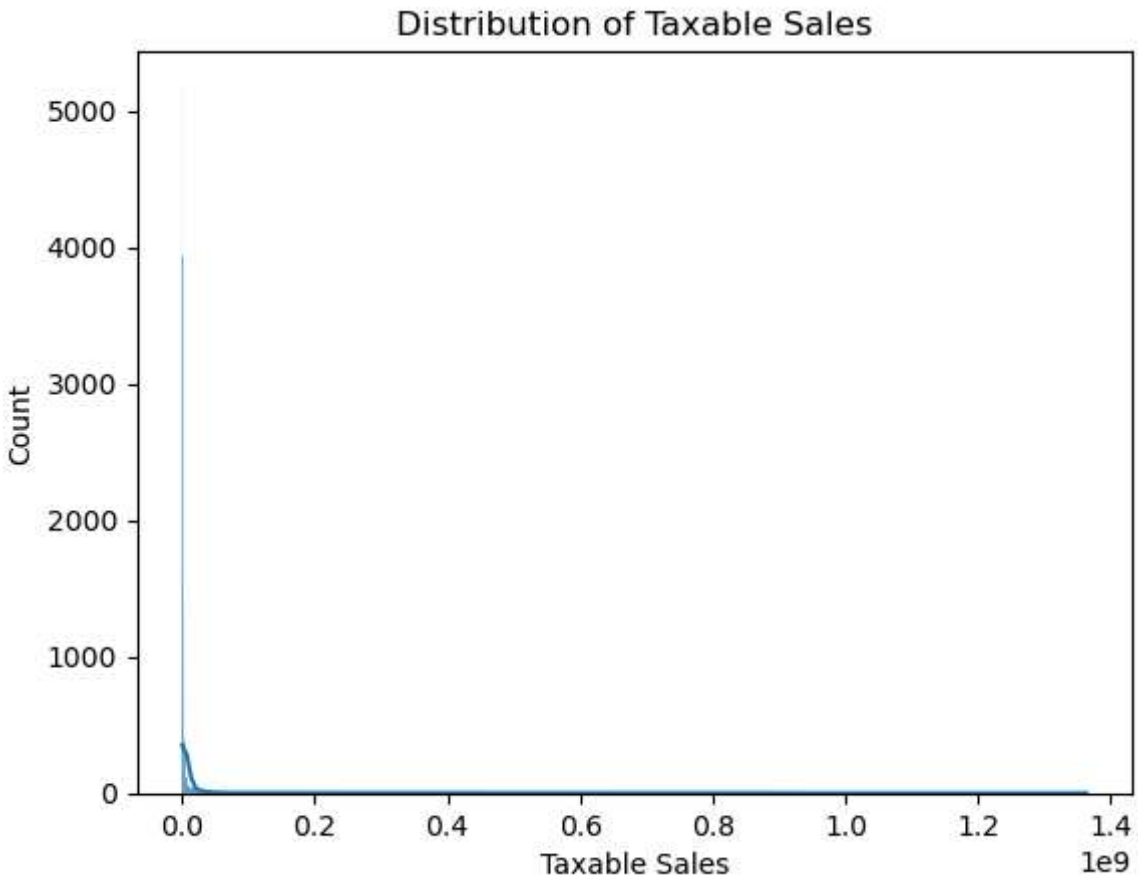
	Fiscal Year	Quarter Ending	County_Number	\
count	41708.000000	41708	41708.000000	
mean	2017.731826	2017-11-17 07:42:55.275726336	50.612065	
min	2012.000000	2011-09-30 00:00:00	0.000000	
25%	2015.000000	2014-09-30 00:00:00	25.000000	
50%	2018.000000	2017-12-31 00:00:00	50.000000	
75%	2021.000000	2020-12-31 00:00:00	77.000000	
max	2024.000000	2023-12-31 00:00:00	99.000000	
std	3.645090	NaN	28.380570	

	Number of Returns	Taxable Sales	Computed Tax	Percent of Tax	\
count	41708.000000	4.170800e+04	4.170800e+04	41708.000000	
mean	114.754675	1.208873e+07	7.225693e+05	0.119507	
min	1.000000	0.000000e+00	0.000000e+00	0.000000	
25%	19.000000	4.061832e+05	2.435600e+04	0.000000	
50%	35.000000	1.146018e+06	6.870100e+04	0.010000	
75%	78.000000	3.515262e+06	2.103382e+05	0.030000	
max	12086.000000	1.363506e+09	8.125367e+07	10.550000	
std	351.785716	5.907319e+07	3.529844e+06	0.582563	

	FIPS County Code	Primary Lat Dec	Primary Long Dec	Year	\
count	41708.000000	41708.000000	41708.000000	41708.000000	
mean	19100.237173	42.101766	-93.370975	2017.237508	
min	19001.000000	40.399828	-96.604626	2011.000000	
25%	19049.000000	41.557301	-94.696415	2014.000000	
50%	19099.000000	42.078948	-93.327364	2017.000000	
75%	19153.000000	42.735494	-91.949987	2020.000000	
max	19197.000000	43.500060	-90.193078	2023.000000	
std	56.754768	0.775510	1.617595	3.628653	

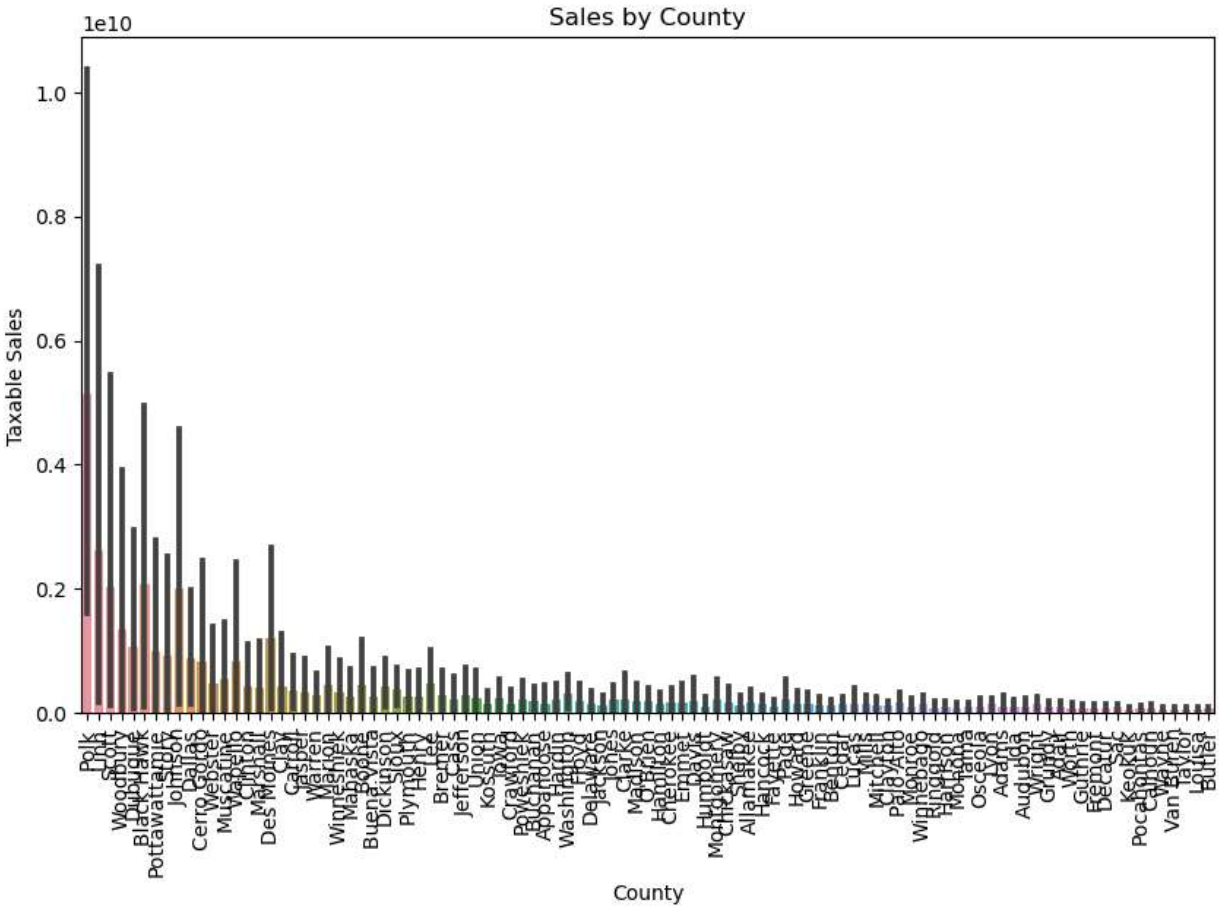
	Quarter
count	41708.000000
mean	2.581303
min	1.000000
25%	2.000000
50%	3.000000
75%	4.000000
max	4.000000
std	1.125659

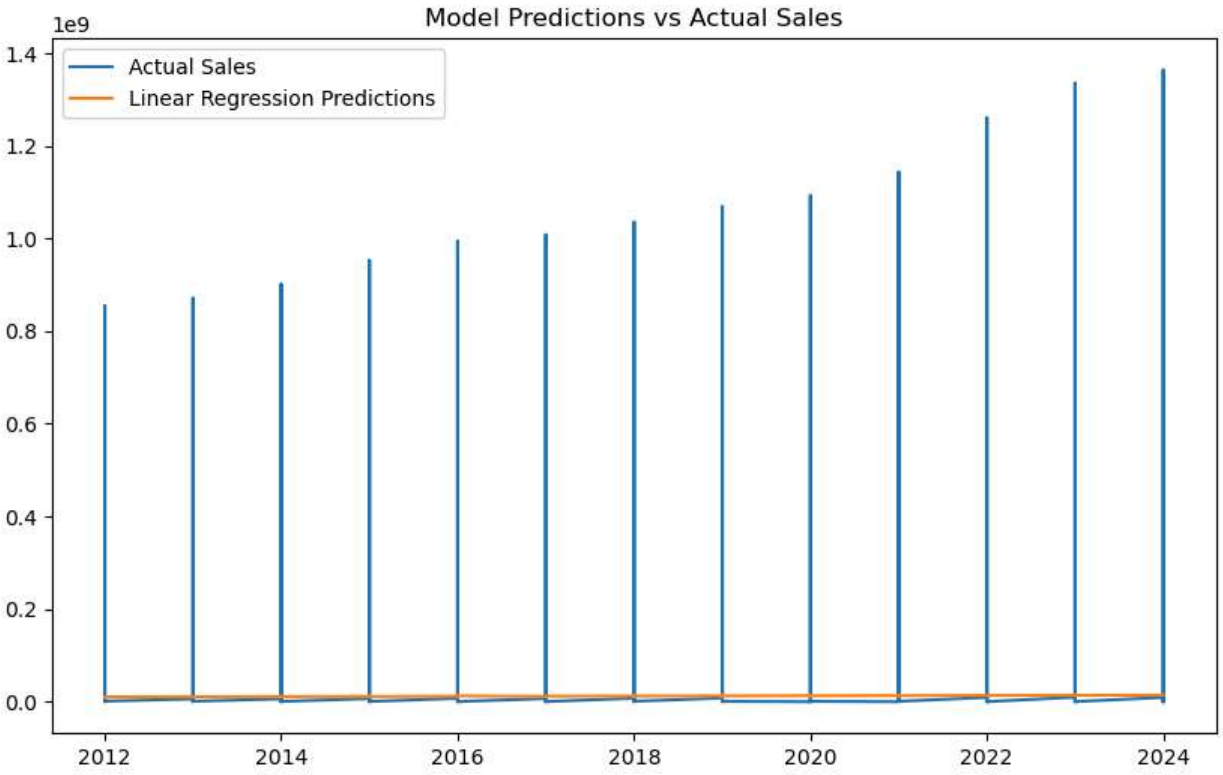
```
C:\Users\vidya\anaconda3\lib\site-packages\seaborn\_oldcore.py:1119: FutureWarning: u
se_inf_as_na option is deprecated and will be removed in a future version. Convert in
f values to NaN before operating instead.
  with pd.option_context('mode.use_inf_as_na', True):
```


Distribution of Taxable Sales
Count
5000
4000
3000
2000
1000
0
0.0
0.2
0.4
0.6
0.8
1.0
1.2
1.4
Taxable Sales
1e9

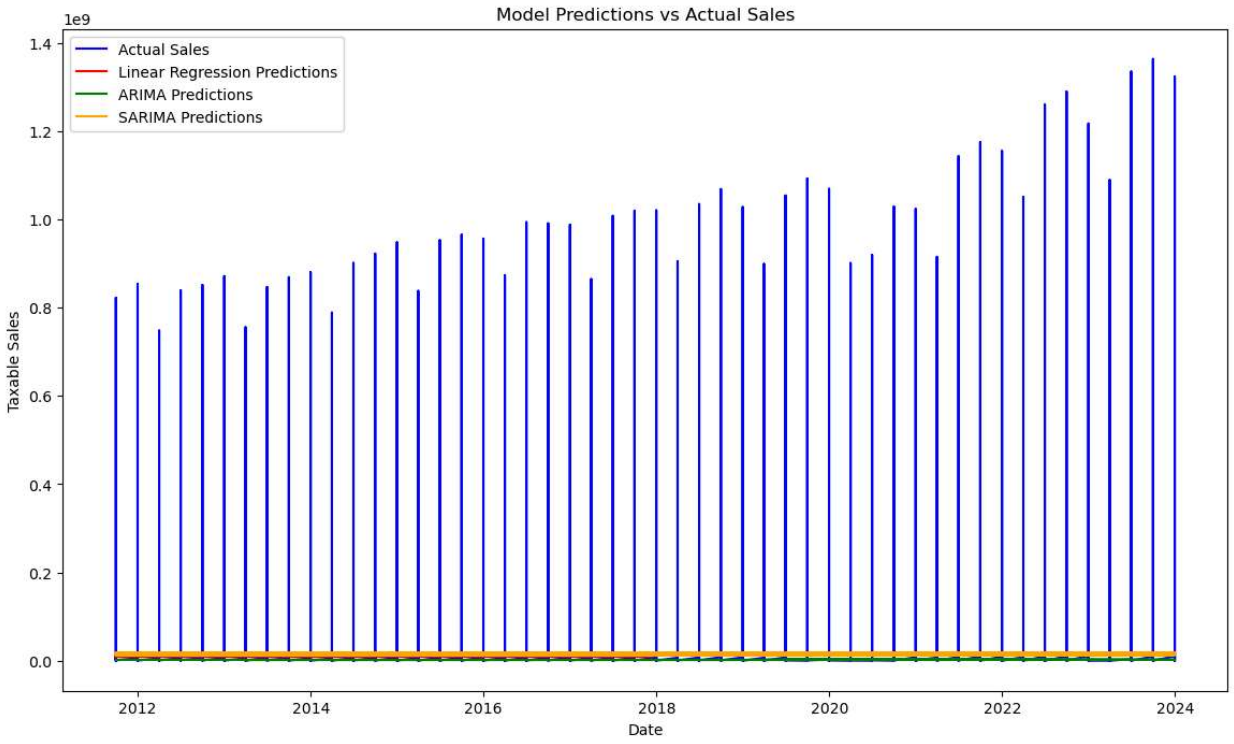
```
  County         City  Taxable Sales
0  Adair        Adair   1.429378e+08
1  Adair  Bridgewater   1.391065e+07
2  Adair        Casey   1.312571e+06
3  Adair   Fontanelle   4.757781e+07
4  Adair   Greenfield   3.696812e+08
       County          City  Taxable Sales  Rank
742      Polk    Des Moines   4.971602e+10   1.0
563      Linn  Cedar Rapids   4.064138e+10   2.0
804     Scott     Davenport   2.729400e+10   3.0
975  Woodbury    Sioux City   2.036445e+10   4.0
298   Dubuque       Dubuque   1.471034e+10   5.0
Linear Regression MAE: 17733952.784922604, MSE: 3355538468229638.5, RMSE: 57927009.83
3320744
                               SARIMAX Results
==============================================================================
Dep. Variable:          Taxable Sales   No. Observations:                41708
Model:                 ARIMA(5, 1, 0)   Log Likelihood             -807028.402
Date:                Sun, 14 Jul 2024   AIC                        1614068.805
Time:                        17:35:41   BIC                        1614120.635
Sample:                             0   HQIC                       1614085.178
                                - 41708
Covariance Type:                  opg
==============================================================================
                 coef    std err          z      P>|z|      [0.025      0.975]
------------------------------------------------------------------------------
ar.L1         -0.6803      0.002   -314.924      0.000      -0.685      -0.676
ar.L2         -0.5123      0.003   -157.740      0.000      -0.519      -0.506
ar.L3         -0.3734      0.003   -107.561      0.000      -0.380      -0.367
ar.L4         -0.2643      0.003    -85.503      0.000      -0.270      -0.258
ar.L5         -0.1504      0.002    -65.954      0.000      -0.155      -0.146
sigma2      3.756e+15   1.77e-19   2.13e+34      0.000    3.76e+15    3.76e+15
===================================================================================
Ljung-Box (L1) (Q):                  14.37   Jarque-Bera (JB):          34469084.05
Prob(Q):                              0.00   Prob(JB):                         0.00
Heteroskedasticity (H):               1.59   Skew:                             9.65
Prob(H) (two-sided):                  0.00   Kurtosis:                       142.51
===================================================================================

Warnings:
[1] Covariance matrix calculated using the outer product of gradients (complex-step).
[2] Covariance matrix is singular or near-singular, with condition number 4.66e+48. S
tandard errors may be unstable.
                                    SARIMAX Results
==========================================================================================
=====
Dep. Variable:                       Taxable Sales   No. Observations:
41708
Model:             SARIMAX(1, 1, 1)x(1, 1, 1, 12)   Log Likelihood             -81037
1.104
Date:                              Sun, 14 Jul 2024   AIC                         162075
2.209
Time:                                    17:38:37   BIC                         162079
5.400
Sample:                                         0   HQIC                        162076
5.853
                                          - 41708
Covariance Type:                            opg
==============================================================================
                 coef    std err          z      P>|z|      [0.025      0.975]
```

```
------------------------------------------------------------------------------
ar.L1          0.1983      0.007     28.392      0.000       0.185       0.212
ma.L1         -0.9996      0.001  -1094.242      0.000      -1.001      -0.998
ar.S.L12       0.0077      0.026      0.295      0.768      -0.043       0.058
ma.S.L12      -0.9998      0.002   -535.724      0.000      -1.003      -0.996
sigma2      7.928e+15   1.03e-17   7.71e+32      0.000    7.93e+15    7.93e+15
==============================================================================
Ljung-Box (L1) (Q):                   2.62   Jarque-Bera (JB):          53105440.05
Prob(Q):                              0.11   Prob(JB):                         0.00
Heteroskedasticity (H):               1.61   Skew:                            11.71
Prob(H) (two-sided):                  0.00   Kurtosis:                       176.26
==============================================================================

Warnings:
[1] Covariance matrix calculated using the outer product of gradients (complex-step).
[2] Covariance matrix is singular or near-singular, with condition number 1.26e+47. S
tandard errors may be unstable.
```





In [9]:
```
# Visualization
plt.figure(figsize=(14, 8))

# Plot actual sales
plt.plot(data['Quarter Ending'], data['Taxable Sales'], label='Actual Sales', color='b

# Plot Linear Regression predictions
test_dates = data.iloc[X_test.index]['Quarter Ending']
plt.plot(test_dates, y_pred_lr, label='Linear Regression Predictions', color='red')

# Plot ARIMA predictions
plt.plot(test_dates, arima_pred, label='ARIMA Predictions', color='green')

# Plot SARIMA predictions
plt.plot(test_dates, sarima_pred, label='SARIMA Predictions', color='orange')

plt.legend()
plt.title('Model Predictions vs Actual Sales')
plt.xlabel('Date')
plt.ylabel('Taxable Sales')
plt.show()
```


Model Predictions vs Actual Sales
1e9
Actual Sales
Linear Regression Predictions
ARIMA Predictions
SARIMA Predictions
Taxable Sales
Date
0.0
0.2
0.4
0.6
0.8
1.0
1.2
1.4
2012
2014
2016
2018
2020
2022
2024

In [ ]: