Stat 5814 Homework 4

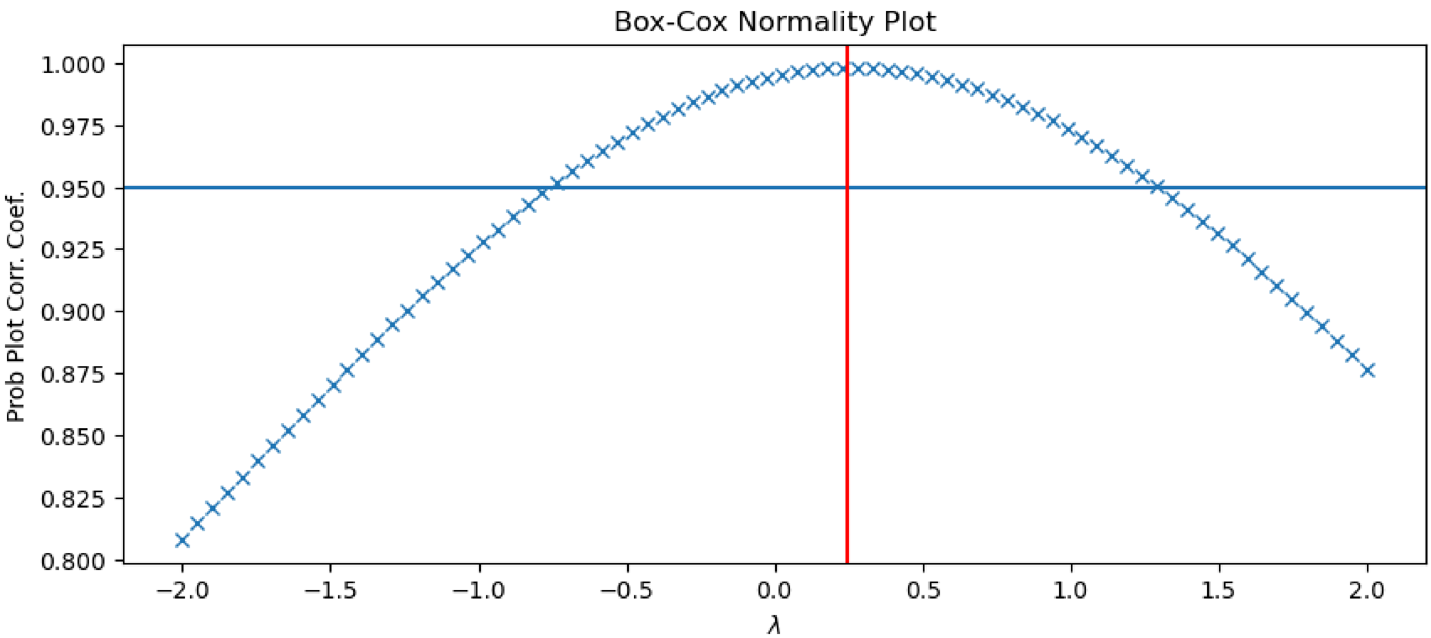
5.14

Setup

```
# 5.14 setup
data = pd.read_csv("../datasets/larain.dat")
data.index = pd.date_range(
    "1878", periods=len(data), freq="Y"
).year  # add timestamp from exhibit 1.1
```

A

```
fig = plt.figure(figsize=(10, 4))
ax = fig.add_subplot()
transform, lambda_fit = stats.boxcox(data["larain"])
print(f"best lambda = {lambda_fit}")
stats.boxcox_normplot(data["larain"], -2, 2, plot=ax)  # plot the fitted values
ax.axhline(0.95)  # confidence interval
ax.axvline(lambda_fit, color="r")  # plot best lambda value
```

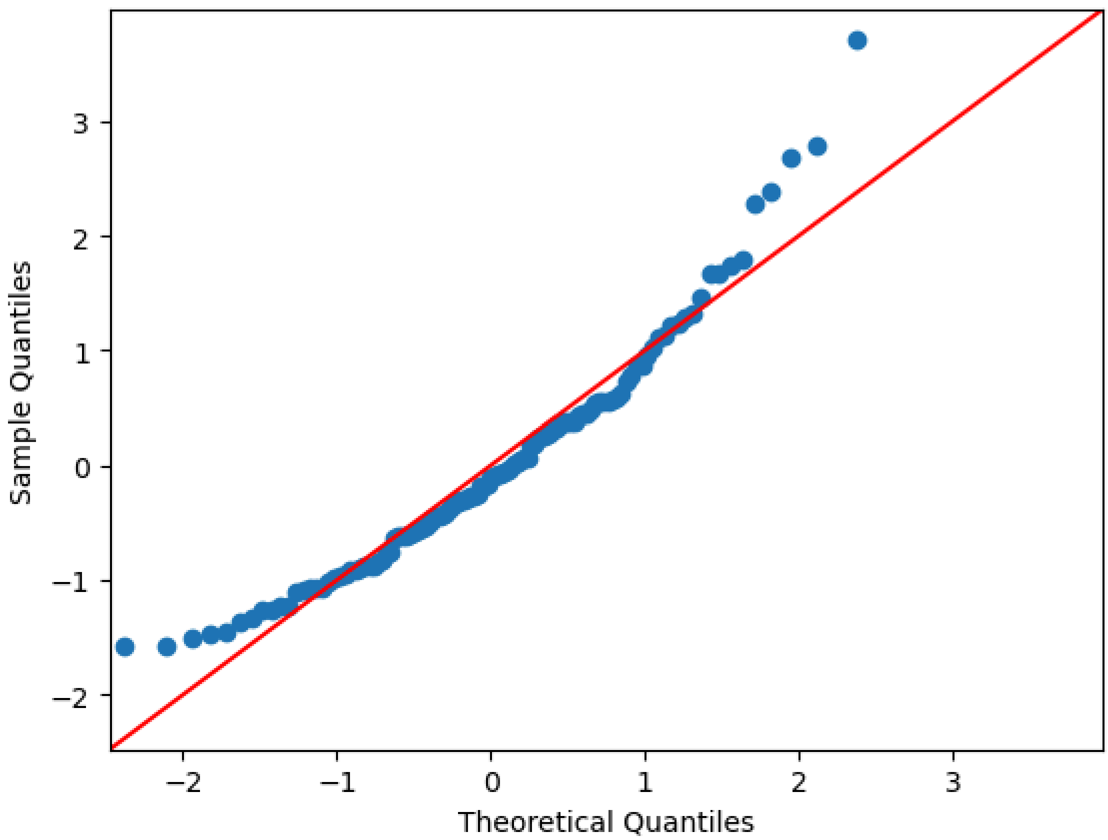


The best value of lambda was found to be 0.246

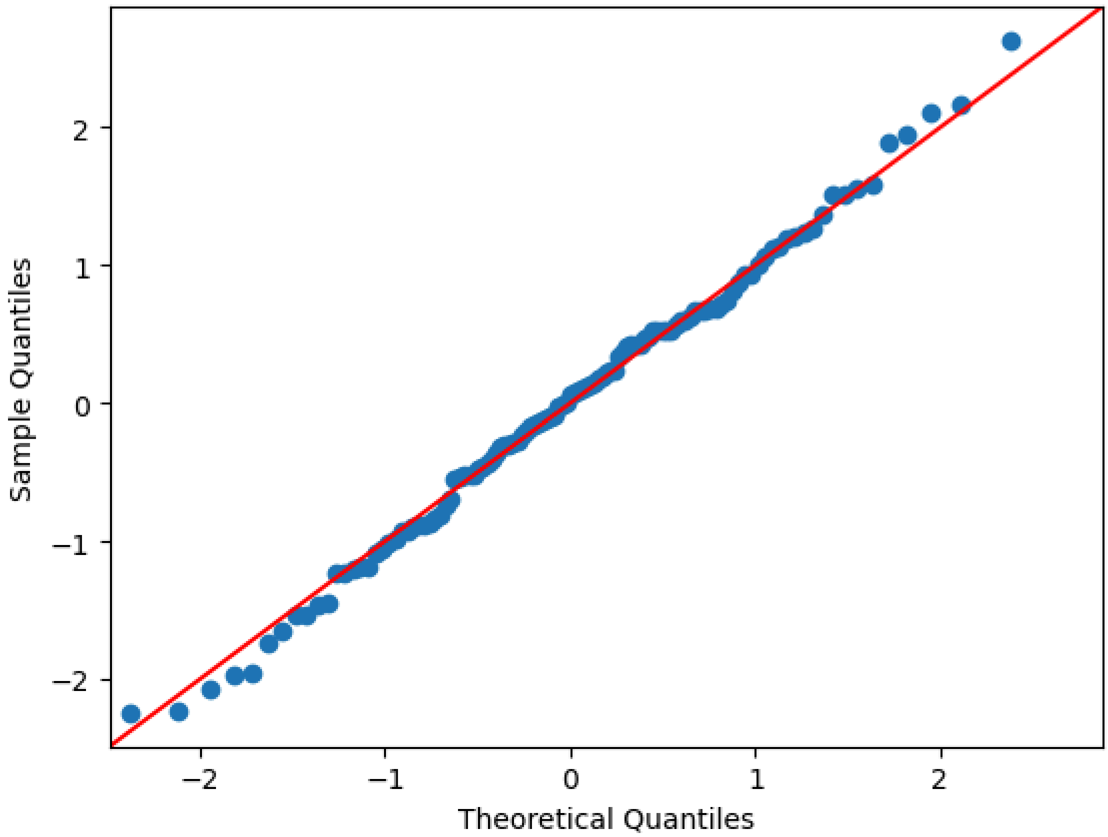
B

```
sm.qqplot(data["larain"], fit=True, line="45") # original plot
sm.qqplot(transform, fit=True, line="45") #transformed plot
```

QQ plot of the original dataset:



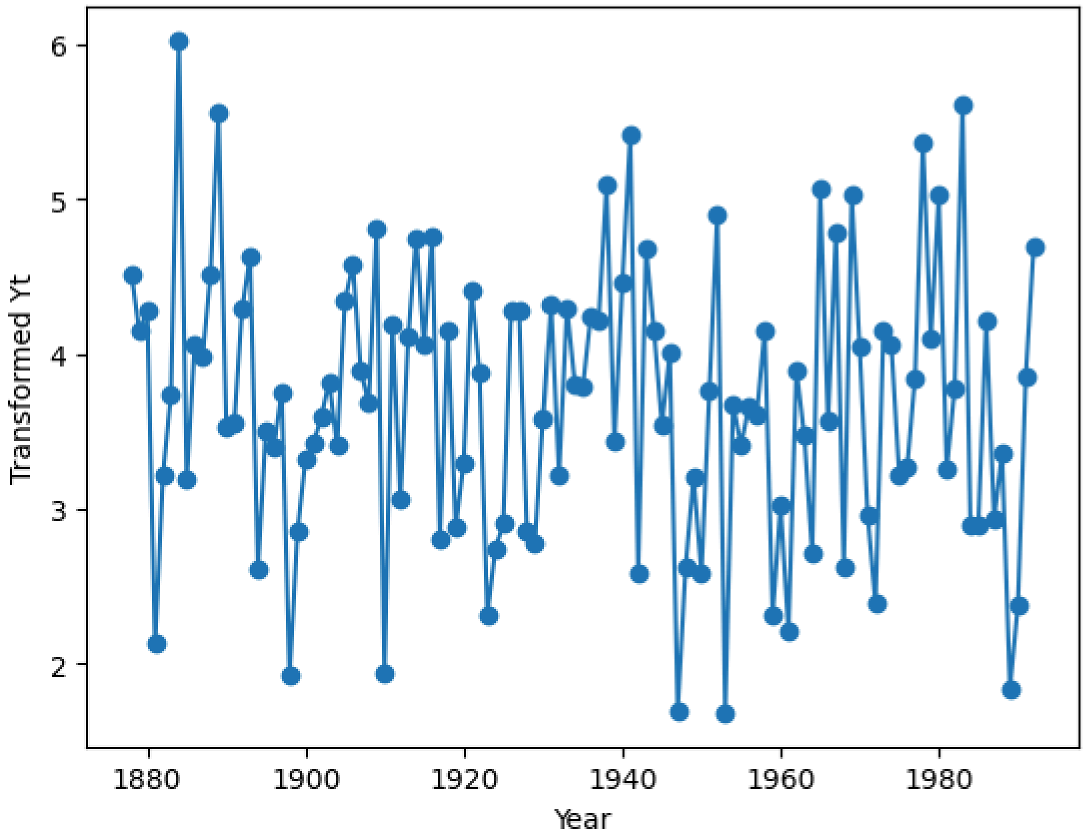
QQ plot of the transformed dataset:



From these plots, we see that the transformed data more closely follows a normal distribution than the original dataset.

C

```
data["transform_values"] = transform
plt.xlabel("Year")
plt.ylabel("Transformed Yt")
plt.plot(data.index, data["transform_values"], marker="o")
```

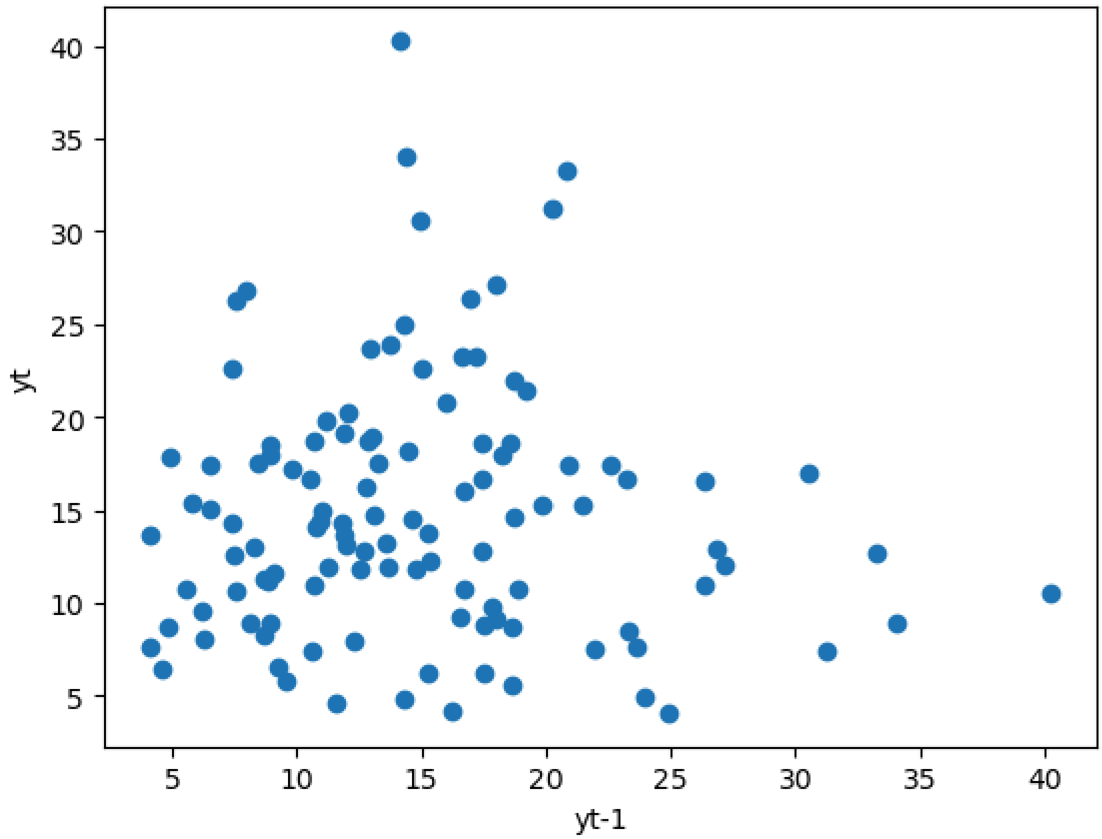


D

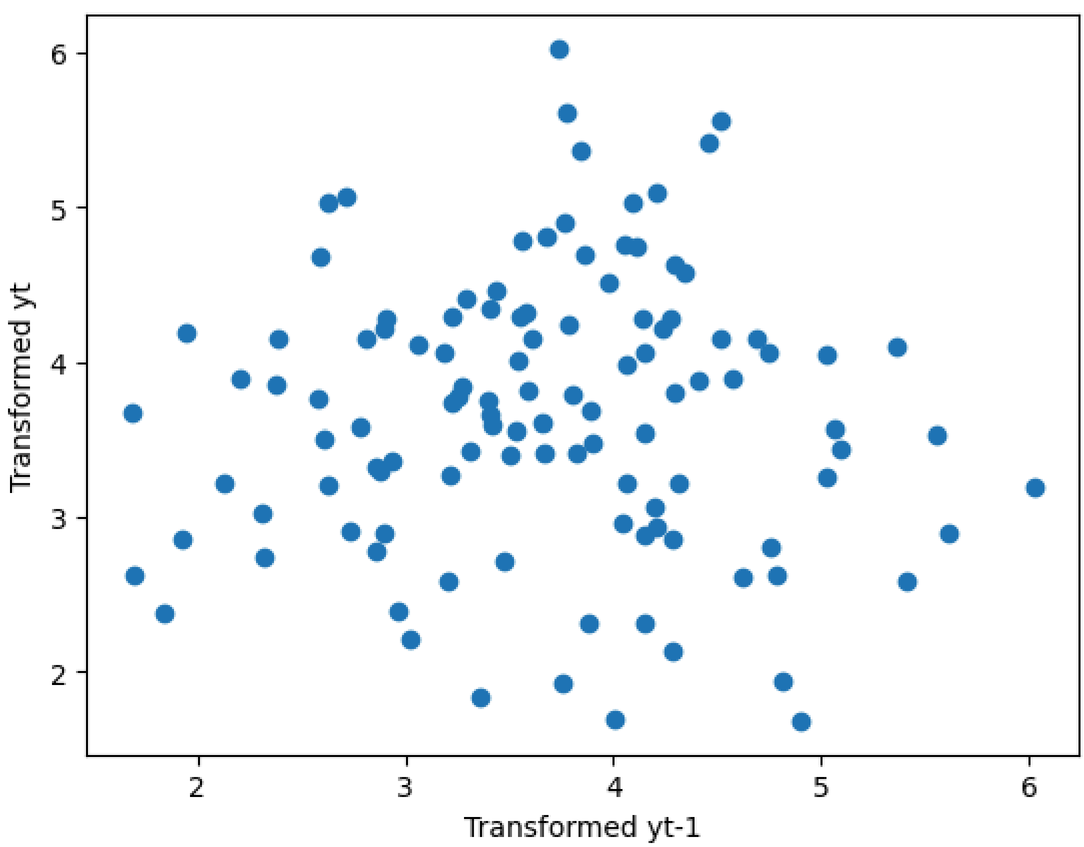
```
data["larain_shift"] = data["larain"].shift(1) # get yt-1
plt.xlabel("yt-1")
plt.ylabel("yt")
plt.plot(data["larain_shift"], data["larain"], marker="o", linestyle='none')

plt.figure()
data["shifted_transformed_values"] = data["transform_values"].shift(1) # get yt-1
plt.xlabel("Transformed yt-1")
plt.ylabel("Transformed yt")
plt.plot(data["shifted_transformed_values"], data["transform_values"], marker="o", lines
```

Original Y_{t-1} vs Y_t plot:



Transformed Y_{t-1} vs Y_t plot:



Comparing these plots, we can see that the dependence of Y_t on previous values of itself has not been affected by the transformation

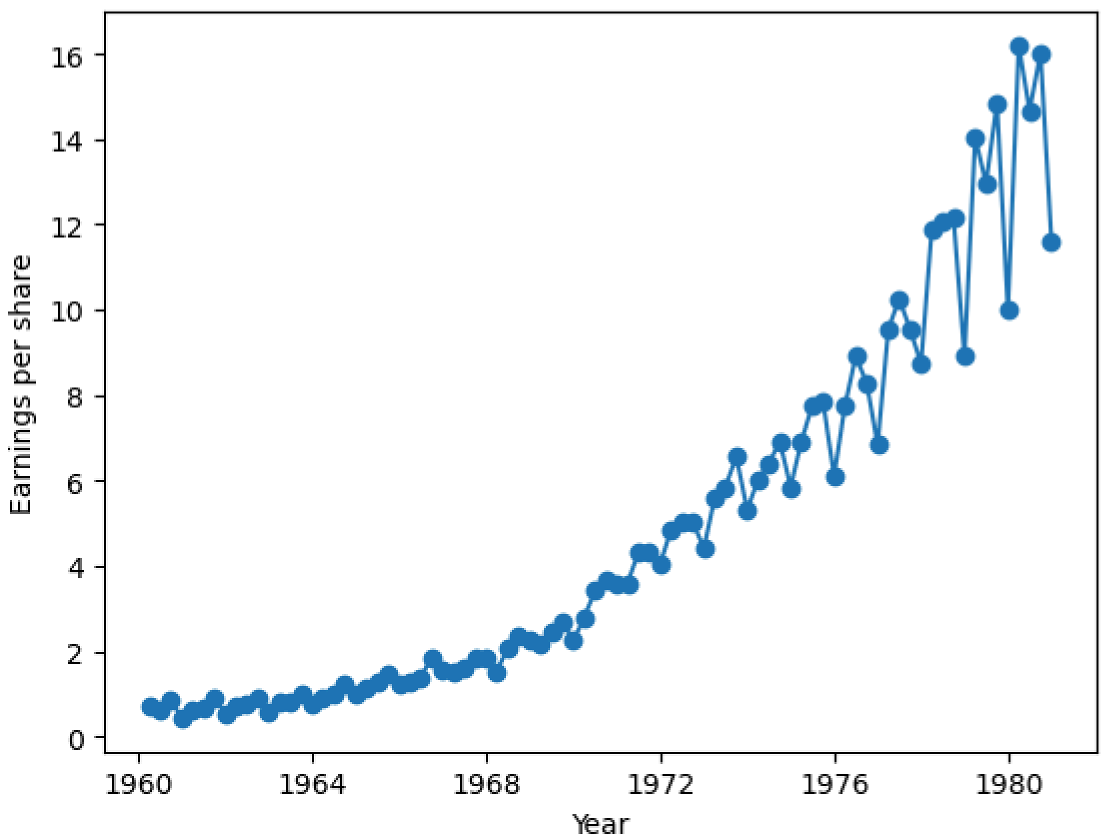
5.15

Setup

```
data = pd.read_csv("../datasets/JJ.dat")
data.index = pd.date_range("1960-01", periods=len(data), freq="Q")
```

A

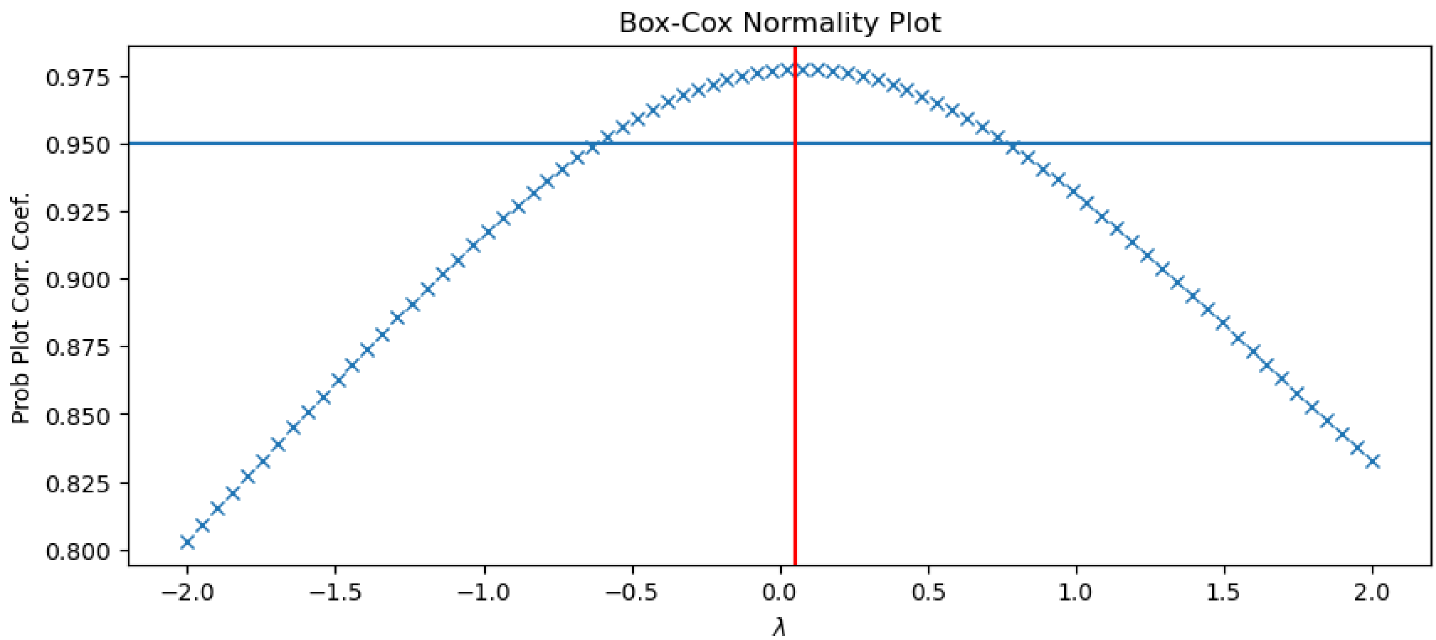
```
plt.plot(data.index, data["JJ"], marker="o")
plt.ylabel("Earnings per share")
plt.xlabel("Year")
```



The data exhibits seasonality and is exponentially increasing

B

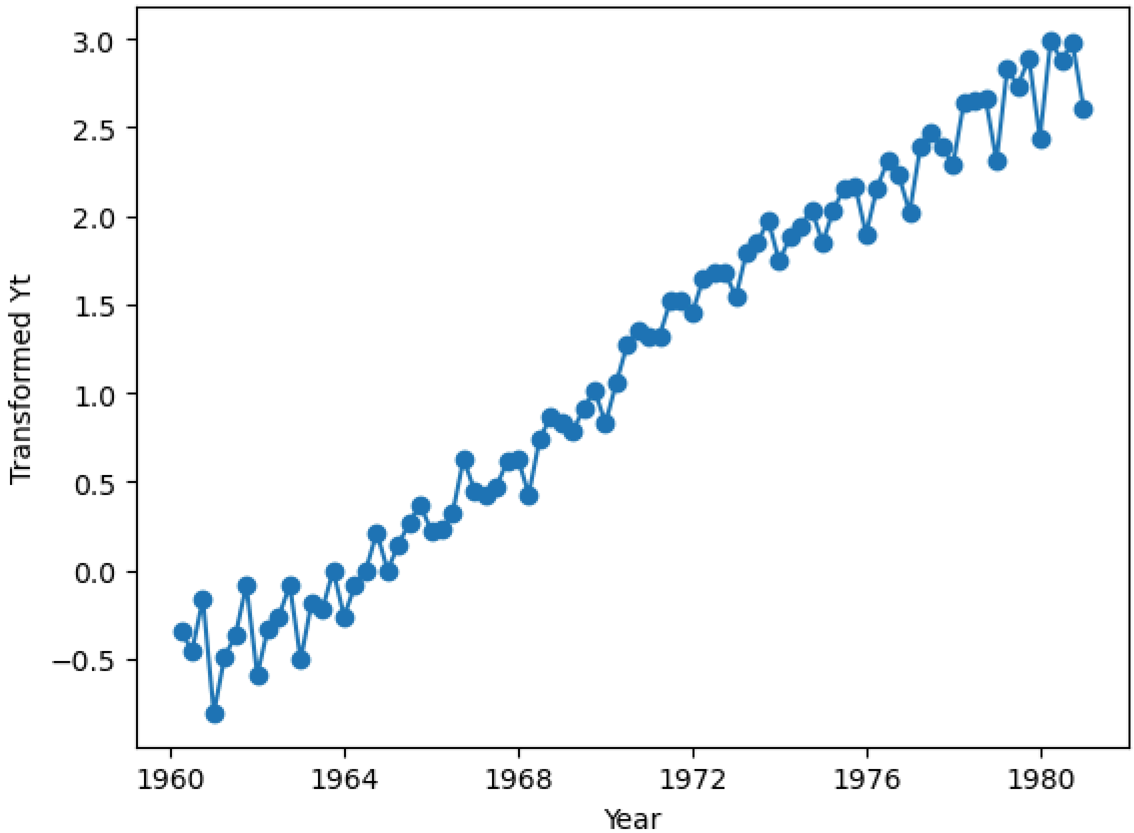
```
fig = plt.figure(figsize=(10, 4))
ax = fig.add_subplot()
transform, lambda_fit = stats.boxcox(data["JJ"])
print(f"best lambda = {lambda_fit}")
stats.boxcox_normplot(data["JJ"], -2, 2, plot=ax)  # plot the fitted values
ax.axhline(0.95)  # confidence interval
ax.axvline(lambda_fit, color="r")  # plot best lambda value
```



The best value of lambda was found to be 0.051

C

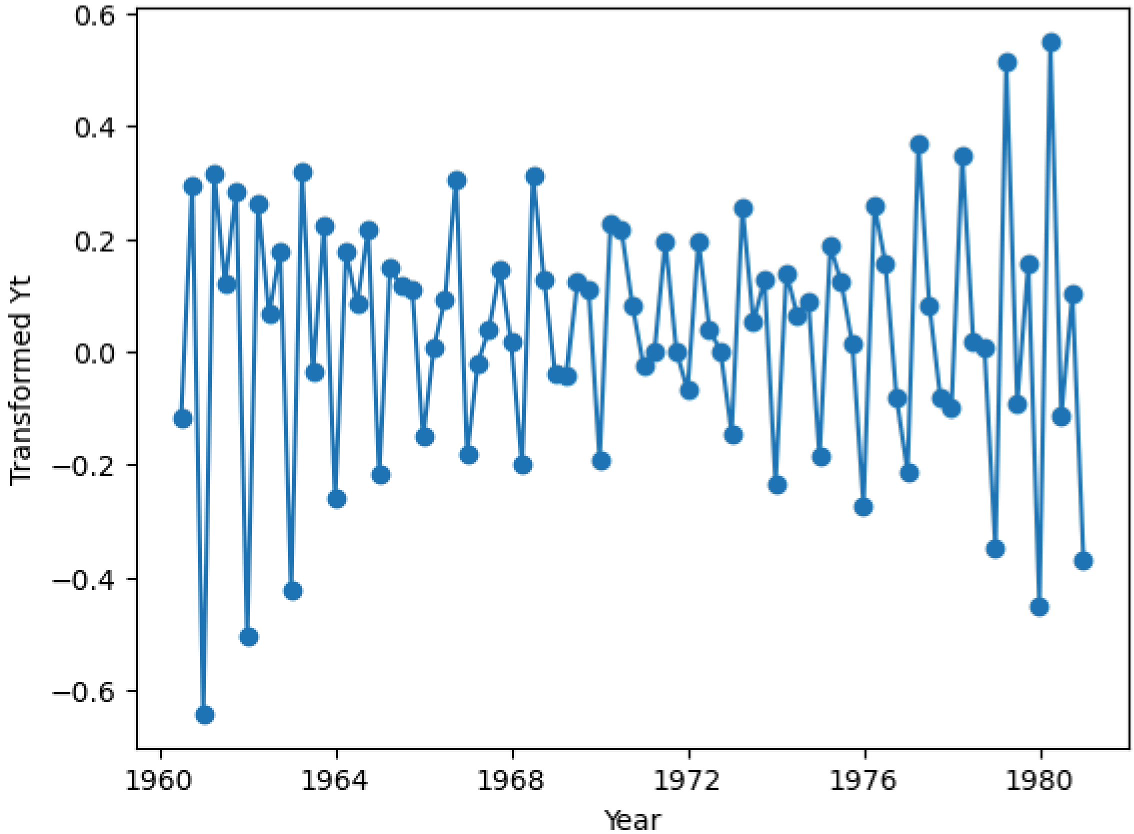
```
data["transform_values"] = transform
plt.xlabel("Year")
plt.ylabel("Transformed Yt")
plt.plot(data.index, data["transform_values"], marker="o")
```



No, this plot does not suggest that a stationary model is appropriate because the transformed data still contain a linearly increasing trend and exhibit a small degree of seasonality.

D

```
diff = data["transform_values"].diff().dropna()
plt.xlabel("Year")
plt.ylabel("Transformed Yt")
plt.plot(data.index[1:], diff, marker="o")
```



The linear trend from the previous plot is removed but there stilll appears to be some seasonal pattern in the differenced values. This data may need to be differenced twice before a stationary model can be fit.