Homework 3 - Submission 2 Yvonna Smothers Load Data In [2]: import pandas as pd import numpy as np import matplotlib.pyplot as plt import seaborn as sns import statsmodels.api as sm import statsmodels.formula.api as smf # Read output datasets full\_tax\_burden\_data = pd.read\_csv('/Users/yvonnasmothers/Documents/GitHub/Homework 3/Homework-3/data/output/TaxBurden\_Data.csv',low\_memory=False, sep="\t") 1. Present a bar graph showing the proportion of states with a change in their cigarette tax in each year from 1970 to 1985. In [3]: # Filter for 1970-1985 data\_1970\_1985 = full\_tax\_burden\_data[(full\_tax\_burden\_data["Year"] >= 1970) & (full\_tax\_burden\_data["Year"] <= 1985)].copy() # Sort values for comparison data\_1970\_1985.sort\_values(by=["state", "Year"], inplace=True) # Identify tax changes data\_1970\_1985["tax\_change"] = data\_1970\_1985.groupby("state")["tax\_dollar"].diff().ne(0) # Compute proportion of states with tax changes per year tax\_change\_proportion = data\_1970\_1985.groupby("Year")["tax\_change"].mean() # Plot the bar graph plt.figure(figsize=(10, 5)) plt.bar(tax\_change\_proportion.index, tax\_change\_proportion.values, color="blue", alpha=0.7) plt.xlabel("Year") plt.ylabel("Proportion of States with Tax Change") plt.title("Proportion of States with a Change in Cigarette Tax (1970-1985)") plt.xticks(rotation=45) plt.show() Proportion of States with a Change in Cigarette Tax (1970-1985) 1.0 Proportion of States with Tax Change 2970 Year 2. Plot on a single graph the average tax (in 2012 dollars) on cigarettes and the average price of a pack of cigarettes from 1970 to 2018. In [4]: # Filter for 1970-2018 data\_1970\_2018 = full\_tax\_burden\_data[(full\_tax\_burden\_data["Year"] >= 1970) & (full\_tax\_burden\_data["Year"] <= 2018)].copy() # Compute averages avg\_tax = data\_1970\_2018.groupby("Year")["tax\_dollar"].mean() avg\_price = data\_1970\_2018.groupby("Year")["cost\_per\_pack"].mean() # Plot plt.figure(figsize=(10, 5)) plt.plot(avg\_tax.index, avg\_tax.values, label="Average Tax (2012 dollars)", color="red") plt.plot(avg\_price.index, avg\_price.values, label="Average Price per Pack", color="blue") plt.xlabel("Year") plt.ylabel("Dollars") plt.title("Average Cigarette Tax and Price (1970-2018)") plt.legend() plt.grid(True) plt.show() Average Cigarette Tax and Price (1970-2018) Average Tax (2012 dollars) Average Price per Pack 6 5 2 1 1970 1980 1990 2000 2010 2020 Year 3. Identify the 5 states with the highest increases in cigarette prices (in dollars) over the time period. Plot the average number of packs sold per capita for those states from 1970 to 2018. In [5]: # Compute price difference for each state price\_diff = full\_tax\_burden\_data.groupby("state")["cost\_per\_pack"].agg(lambda x: x.iloc[-1] - x.iloc[0]) # Identify top 5 and bottom 5 states top5\_states = price\_diff.nlargest(5).index bottom5\_states = price\_diff.nsmallest(5).index # Filter data for those states data\_top5 = full\_tax\_burden\_data[full\_tax\_burden\_data["state"].isin(top5\_states)] data\_bottom5 = full\_tax\_burden\_data[full\_tax\_burden\_data["state"].isin(bottom5\_states)] # Compute average packs sold per capita for top 5 states top5\_sales = data\_top5.groupby("Year")["sales\_per\_capita"].mean() # Compute average packs sold per capita for bottom 5 states bottom5\_sales = data\_bottom5.groupby("Year")["sales\_per\_capita"].mean() # Plot sales trends plt.figure(figsize=(10, 5)) plt.plot(top5\_sales.index, top5\_sales.values, label="Top 5 States", color="green") plt.plot(bottom5\_sales.index, bottom5\_sales.values, label="Bottom 5 States", color="orange") plt.xlabel("Year") plt.ylabel("Packs Sold per Capita") plt.title("Comparison of Sales Trends (Top vs Bottom 5 States)") plt.legend() plt.grid(True) plt.show() Comparison of Sales Trends (Top vs Bottom 5 States) Top 5 States 140 Bottom 5 States 120 Packs Sold per Capita 60 20 1970 1980 1990 2000 2010 2020 Year 4. Identify the 5 states with the lowest increases in cigarette prices over the time period. Plot the average number of packs sold per capita for those states from 1970 to 2018. In [6]: # Filter data for 1970-1990 data\_1970\_1990 = full\_tax\_burden\_data[(full\_tax\_burden\_data["Year"] >= 1970) & (full\_tax\_burden\_data["Year"] <= 1990)].copy() # Take logs data\_1970\_1990["log\_sales"] = np.log(data\_1970\_1990["sales\_per\_capita"]) data\_1970\_1990["log\_price"] = np.log(data\_1970\_1990["cost\_per\_pack"]) # OLS regression: log\_sales ~ log\_price X = sm.add\_constant(data\_1970\_1990["log\_price"]) y = data\_1970\_1990["log\_sales"] model = sm.OLS(y, X).fit() # Display results print (model.summary()) OLS Regression Results \_\_\_\_\_\_ Dep. Variable: log\_sales R-squared: Model:

Model:

Method:

Date:

Date:

Med, 19 Mar 2025

Date:

Date:

Med, 19 Mar 2025

Date:

Dog\_sales

R-squared:

O.125

Adj. R-squared:

153.9

Prob (F-statistic):

4.18e-33

Time:

Date:

Dat No. Observations: 1071 AIC:
Df Residuals: 1069 BIC: -294.0 1071 AIC: -284.0 Df Model: 1 Covariance Type: nonrobust coef std err t P>|t| [0.025 0.975] const 4.7504 0.008 585.321 0.000 4.734 4.766 log\_price -0.1715 0.014 -12.404 0.000 -0.199 -0.144 Omnibus: 64.611 Durbin-Watson: 0.139 

 Prob (Omnibus):
 0.000
 Jarque-Bera (JB):
 224.414

 Skew:
 0.173
 Prob (JB):
 1.86e-49

 Kurtosis:
 5.216
 Cond. No.
 2.48

 Notes: [1] Standard Errors assume that the covariance matrix of the errors is correctly specified. 5. Compare the trends in sales from the 5 states with the highest price increases to those with the lowest price increases. 6. Focusing only on the time period from 1970 to 1990, regress log sales on log prices to estimate the price elasticity of demand over that period. Interpret your results. In [7]: # Filter data for 1970-1990 data\_1970\_1990 = full\_tax\_burden\_data[(full\_tax\_burden\_data["Year"] >= 1970) & (full\_tax\_burden\_data["Year"] <= 1990)].copy() # Take logs data\_1970\_1990["log\_sales"] = np.log(data\_1970\_1990["sales\_per\_capita"]) data\_1970\_1990["log\_price"] = np.log(data\_1970\_1990["cost\_per\_pack"]) # OLS regression: log\_sales ~ log\_price X = sm.add\_constant(data\_1970\_1990["log\_price"]) y = data\_1970\_1990["log\_sales"] model = sm.OLS(y, X).fit() # Display results print (model.summary()) OLS Regression Results \_\_\_\_\_\_ 
 Dep. Variable:
 log\_sales
 R-squared:
 0.126

 Model:
 OLS
 Adj. R-squared:
 0.125

 Method:
 Least Squares
 F-statistic:
 153.9

 Date:
 Wed, 19 Mar 2025
 Prob (F-statistic):
 4.18e-33

 Time:
 07:13:56
 Log-Likelihood:
 148.99

 No. Observations:
 1071
 AIC:
 -294.0
 No. Observations: 1071 AIC:
Df Residuals: 1069 BIC:
Df Model: 1 -284.0 Covariance Type: nonrobust \_\_\_\_\_\_ coef std err t P>|t| [0.025 0.975] const 4.7504 0.008 585.321 0.000 4.734 4.766 \_\_\_\_\_\_ 

 Omnibus:
 64.611
 Durbin-Watson:
 0.139

 Prob(Omnibus):
 0.000
 Jarque-Bera (JB):
 224.414

 Prob (Omnibus):
 0.000
 Jarque-Bera (JB):
 224.414

 Skew:
 0.173
 Prob (JB):
 1.86e-49

 5 216
 Cond No
 2.48

 5.216 Cond. No. \_\_\_\_\_\_ [1] Standard Errors assume that the covariance matrix of the errors is correctly specified. 7. Again limiting to 1970 to 1990, regress log sales on log prices using the total (federal and state) cigarette tax (in dollars) as an instrument for log prices. Interpret your results and compare your estimates to those without an instrument. Are they different? If so, why? 8. Show the first stage and reduced-form results from the instrument. In [8]: # First stage: log price ~ tax dollar X\_iv = sm.add\_constant(data\_1970\_1990["tax\_dollar"]) y\_iv = data\_1970\_1990["log\_price"] first\_stage = sm.OLS(y\_iv, X\_iv).fit() # Get predicted log prices data\_1970\_1990["log\_price\_hat"] = first\_stage.predict(X\_iv) # Second stage: log\_sales ~ log\_price\_hat X\_second = sm.add\_constant(data\_1970\_1990["log\_price\_hat"]) y\_second = data\_1970\_1990["log\_sales"] second\_stage = sm.OLS(y\_second, X\_second).fit() # Display IV regression results print("First Stage Regression:\n", first\_stage.summary()) print("\nSecond Stage (IV) Regression:\n", second\_stage.summary()) First Stage Regression: OLS Regression Results \_\_\_\_\_\_ Dep. Variable: log\_price R-squared: 0.695
Model: OLS Adj. R-squared: 0.694
Method: Least Squares F-statistic: 2431.
Date: Wed, 19 Mar 2025 Prob (F-statistic): 1.52e-277
Time: 07:13:56 Log-Likelihood: -66.026
No. Observations: 1071 AIC: 136.1
Df Residuals: 1069 BIC: 146.0
Df Model: 1
Covariance Type: nonrobust \_\_\_\_\_ coef std err t P>|t| [0.025 0.975] \_\_\_\_\_\_ const -1.4288 0.023 -61.805 0.000 -1.474 -1.383 tax\_dollar 4.1686 0.085 49.300 0.000 4.003 4.334 \_\_\_\_\_\_ 

 Omnibus:
 48.404
 Durbin-Watson:
 0.428

 Prob(Omnibus):
 0.000
 Jarque-Bera (JB):
 54.366

 Skew:
 0.551
 Prob(JB):
 1.57e-12

 Kurtosis:
 2.923
 Cond. No.
 11.5

 \_\_\_\_\_ [1] Standard Errors assume that the covariance matrix of the errors is correctly specified. Second Stage (IV) Regression: OLS Regression Results \_\_\_\_\_\_ 
 Dep. Variable:
 log\_sales
 R-squared:
 0.217

 Model:
 OLS
 Adj. R-squared:
 0.216

 Method:
 Least Squares
 F-statistic:
 296.2

 Date:
 Wed, 19 Mar 2025
 Prob (F-statistic):
 8.91e-59

 Time:
 07:13:56
 Log-Likelihood:
 207.94

 No. Observations:
 1071
 AIC:
 -411.9

 Df Residuals:
 1069
 BIC:
 -401.9

 Df Model:
 1
 -401.9
 Covariance Type: nonrobust \_\_\_\_\_\_ coef std err t P>|t| [0.025 0.975] const 4.7151 0.008 569.228 0.000 4.699 4.731 log\_price\_hat -0.2703 0.016 -17.209 0.000 -0.301 -0.239 \_\_\_\_\_ 

 Omnibus:
 77.756
 Durbin-Watson:
 0.157

 Prob(Omnibus):
 0.000
 Jarque-Bera (JB):
 352.076

 Skew:
 0.115
 Prob(JB):
 3.53e-77

 5.799 Cond. No. \_\_\_\_\_\_ [1] Standard Errors assume that the covariance matrix of the errors is correctly specified. 9. Repeat questions 1-3 focusing on the period from 1991 to 2015 In [9]: # Repeat OLS and IV steps for 1991-2015 data\_1991\_2015 = full\_tax\_burden\_data[(full\_tax\_burden\_data["Year"] >= 1991) & (full\_tax\_burden\_data["Year"] <= 2015)].copy() data\_1991\_2015["log\_sales"] = np.log(data\_1991\_2015["sales\_per\_capita"]) data\_1991\_2015["log\_price"] = np.log(data\_1991\_2015["cost\_per\_pack"]) # OLS X = sm.add\_constant(data\_1991\_2015["log\_price"]) y = data\_1991\_2015["log\_sales"]  $model_ols = sm.OLS(y, X).fit()$ # IV Regression X\_iv = sm.add\_constant(data\_1991\_2015["tax\_dollar"]) y\_iv = data\_1991\_2015["log\_price"] first\_stage\_iv = sm.OLS(y\_iv, X\_iv).fit() data\_1991\_2015["log\_price\_hat"] = first\_stage\_iv.predict(X\_iv) X\_second\_iv = sm.add\_constant(data\_1991\_2015["log\_price\_hat"]) y\_second\_iv = data\_1991\_2015["log\_sales"]

\_\_\_\_\_\_ 
 Dep. Variable:
 log\_sales
 R-squared:
 0.533

 Model:
 OLS
 Adj. R-squared:
 0.532

 Method:
 Least Squares
 F-statistic:
 1451.

 Date:
 Wed, 19 Mar 2025
 Prob (F-statistic):
 1.52e-212

 Time:
 07:13:56
 Log-Likelihood:
 -296.47

 No. Observations:
 1275
 AIC:
 596.9

 Df Residuals:
 1273
 BIC:
 607.2

 Df Model:
 1
 1
 1
 Covariance Type: nonrobust \_\_\_\_\_\_ coef std err t P>|t| [0.025 0.975] const 5.0395 0.023 219.934 0.000 4.995 5.084 log\_price -0.6656 0.017 -38.094 0.000 -0.700 -0.631 \_\_\_\_\_\_ 

 Omnibus:
 19.351
 Durbin-Watson:
 0.158

 Prob(Omnibus):
 0.000
 Jarque-Bera (JB):
 33.046

 Skew:
 0.064
 Prob(JB):
 6.67e-08

 Kurtosis:
 3.778
 Cond. No.
 5.37

 \_\_\_\_\_\_

second\_stage\_iv = sm.OLS(y\_second\_iv, X\_second\_iv).fit()

print("\nIV Regression (1991-2015):\n", second\_stage\_iv.summary())

OLS Regression Results

print("\nOLS (1991-2015):\n", model\_ols.summary())

# Print results

OLS (1991-2015):

[1] Standard Errors assume that the covariance matrix of the errors is correctly specified. IV Regression (1991-2015): OLS Regression Results \_\_\_\_\_\_ 
 Dep. Variable:
 log\_sales
 R-squared:
 0.586

 Model:
 OLS
 Adj. R-squared:
 0.585

 Method:
 Least Squares
 F-statistic:
 1800.

 Date:
 Wed, 19 Mar 2025
 Prob (F-statistic):
 7.64e-246

 Time:
 07:13:56
 Log-Likelihood:
 -219.72

 No. Observations:
 1275
 AIC:
 443.4

 Df Residuals:
 1273
 BIC:
 453.7

 Df Model:
 1
 453.7
 Df Model: 1 Covariance Type: nonrobust \_\_\_\_\_\_ coef std err t P>|t| [0.025 5.2070 0.024 213.370 0.000 5.159 5.255 log\_price\_hat -0.8033 0.019 -42.423 0.000 -0.840 -0.766 \_\_\_\_\_\_ 30.517 Durbin-Watson: Prob(Omnibus): 0.000 Jarque-Bera (JB): 59.349 -0.121 Prob(JB): 1.30e-13 Skew: 4.029 Cond. No. \_\_\_\_\_\_

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

In [10]: print("Elasticity (1970-1990):", model.params["log\_price"])

print("Elasticity (1991-2015):", model\_ols.params["log\_price"])

10. Compare your elasticity estimates from 1970-1990 versus those from 1991-2015. Are they different? If so, why?