Report on the Analysis of OECD's and Non-OECD's Countries Fuel Demand

September 26, 2025

Loadind Data, Styles and Necessary Libraries

In [1]:
```python
# Import necessary libraries
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
from scipy import stats
import warnings
warnings.filterwarnings('ignore')

# Set up plotting style
plt.style.use('seaborn-v0_8')
sns.set_palette("husl")

# Load the data
df = pd.read_excel('Data.xlsx', sheet_name='Data')

# Display basic information about the dataset
print("Dataset shape:", df.shape)
print("\nFirst few rows:")
print(df.head())
print("\nVariable descriptions:")
print(df.info())
```

```
Dataset shape: (106, 10)

First few rows:
     country  oecd code     area         gdppc       pop     fuelcon  \
0    Albania     0  ALB    27400   3700.738525   3204284   63.966255
1    Algeria     0  DZA  2381741   4566.891113  35468208   75.920944
2     Angola     0  AGO  1246700   4237.347656  19081912   34.472725
3  Argentina     0  ARG  2736690   9124.334961  40412376   87.872360
4  Australia     1  AUS  7682300  51628.597656  22065300  313.963562

   fuelprice  oil_rents_gdp  pop_urban
0   6.789734       1.357490   0.000000
1   0.777977      23.375537   6.759854
2   2.046335      39.719702  22.693997
3   5.236047       2.334014  44.155553
4   5.535066       0.772678  59.235835

Variable descriptions:
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 106 entries, 0 to 105
Data columns (total 10 columns):
 #   Column         Non-Null Count  Dtype
---  ------         --------------  -----
 0   country        106 non-null    object
 1   oecd           106 non-null    int64
 2   code           106 non-null    object
 3   area           106 non-null    int64
 4   gdppc          106 non-null    float64
 5   pop            106 non-null    int64
 6   fuelcon        106 non-null    float64
 7   fuelprice      106 non-null    float64
 8   oil_rents_gdp  106 non-null    float64
 9   pop_urban      106 non-null    float64
dtypes: float64(5), int64(3), object(2)
memory usage: 8.4+ KB
None
```

PART 1. Fuel Demand in OECD Countries

In [5]:
```python
# Filter OECD countries
oecd_df = df[df['oecd'] == 1].copy()
non_oecd_df = df[df['oecd'] == 0].copy()

print(f"OECD countries: {len(oecd_df)}")
print(f"Non-OECD countries: {len(non_oecd_df)}")
```

```
# Create scatter plots for OECD countries
fig, axes = plt.subplots(1, 2, figsize=(15, 5))

# Plot 1: Fuel consumption vs Fuel price
axes[0].scatter(oecd_df['fuelprice'], oecd_df['fuelcon'], alpha=0.7)
axes[0].set_xlabel('Fuel Price ($/gallon)')
axes[0].set_ylabel('Fuel Consumption (gallons/capita)')
axes[0].set_title('Figure 1 - OECD: Fuel Consumption vs Price')
axes[0].grid(True, alpha=0.3)

# Plot 2: Fuel consumption vs GDP per capita
axes[1].scatter(oecd_df['gdppc'], oecd_df['fuelcon'], alpha=0.7)
axes[1].set_xlabel('GDP per capita ($)')
axes[1].set_ylabel('Fuel Consumption (gallons/capita)')
axes[1].set_title('Figure 2 - OECD: Fuel Consumption vs GDP per capita')
axes[1].grid(True, alpha=0.3)

plt.tight_layout()
plt.show()

# Regression analysis for OECD countries

# Linear specification
X_linear = oecd_df[['fuelprice', 'gdppc']]
X_linear = sm.add_constant(X_linear)  # Add constant term
y_linear = oecd_df['fuelcon']

model_linear = sm.OLS(y_linear, X_linear).fit()

# Log specification (adding small constant to avoid log(0))
small_constant = 1
X_log = np.log(oecd_df[['fuelprice', 'gdppc']] + small_constant)
X_log = sm.add_constant(X_log)
y_log = np.log(oecd_df['fuelcon'] + small_constant)

model_log = sm.OLS(y_log, X_log).fit()

# Display results
print("="*60)
print("Table 1 - OECD COUNTRIES REGRESSION RESULTS")
print("="*60)

print("\nLINEAR SPECIFICATION:")
print(model_linear.summary())

print("\n\nLOG-LOG SPECIFICATION:")
print(model_log.summary())
```

```
OECD countries: 33
Non-OECD countries: 73
```

```
============================================================
Table 1 - OECD COUNTRIES REGRESSION RESULTS
============================================================

LINEAR SPECIFICATION:
                            OLS Regression Results
==============================================================================
Dep. Variable:                fuelcon   R-squared:                       0.646
Model:                            OLS   Adj. R-squared:                  0.622
Method:                 Least Squares   F-statistic:                     27.38
Date:                Fri, 26 Sep 2025   Prob (F-statistic):           1.71e-07
Time:                        15:18:08   Log-Likelihood:                -176.16
No. Observations:                  33   AIC:                             358.3
Df Residuals:                      30   BIC:                             362.8
Df Model:                           2
Covariance Type:            nonrobust

==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
const        340.8755     51.397      6.632      0.000     235.909     445.842
fuelprice    -37.9354      7.413     -5.118      0.000     -53.074     -22.797
gdppc          0.0035      0.001      6.421      0.000       0.002       0.005
==============================================================================
Omnibus:                        0.542   Durbin-Watson:                   1.963
Prob(Omnibus):                  0.763   Jarque-Bera (JB):                0.045
Skew:                          -0.006   Prob(JB):                        0.978
Kurtosis:                       3.181   Cond. No.                     2.20e+05
==============================================================================

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
[2] The condition number is large, 2.2e+05. This might indicate that there are
strong multicollinearity or other numerical problems.


LOG-LOG SPECIFICATION:
                            OLS Regression Results
==============================================================================
Dep. Variable:                fuelcon   R-squared:                       0.794
Model:                            OLS   Adj. R-squared:                  0.780
Method:                 Least Squares   F-statistic:                     57.81
Date:                Fri, 26 Sep 2025   Prob (F-statistic):           5.11e-11
Time:                        15:18:08   Log-Likelihood:                 7.0669
No. Observations:                  33   AIC:                            -8.134
Df Residuals:                      30   BIC:                            -3.644
Df Model:                           2
Covariance Type:            nonrobust
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
const          0.8762      0.690      1.270      0.214      -0.533       2.285
fuelprice     -1.1774      0.199     -5.904      0.000      -1.585      -0.770
gdppc          0.6546      0.064     10.168      0.000       0.523       0.786
==============================================================================
Omnibus:                        0.039   Durbin-Watson:                   1.941
Prob(Omnibus):                  0.981   Jarque-Bera (JB):                0.183
Skew:                           0.071   Prob(JB):                        0.913
Kurtosis:                       2.664   Cond. No.                         206.
==============================================================================

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

DISCUSSION OF PART 1:

I began the analysis restricting the dataset to OECD countries (n = 33).

Then, I generated the two scatter plots to visualize the relationships:

- The scatter plot in **Figure 1** shows a clear negative relationship. In OECD countries, as fuel price increases, fuel consumption per capita tends to decrease. This is consistent with basic economic theory, where higher prices lead to reduced quantity demanded.
- The scatter plot in **Figure 2** reveals a positive relationship. OECD countries with higher GDP per capita tend to consume more fuel per person. This suggests that as income rises, demand for fuel (likely for transportation and other energy-intensive activities) also increases.

Regression Analysis Results: I estimated the two regression models for the OECD sample: a linear specification and a log-log (elasticity) specification, and the results are in **Table 1.**

Linear Specification: **fuelcon = β0 + β1 * fuelprice + β2 * gdppc + ε**

- The coefficient for **fuelprice** is negative (**-37.94**) and statistically significant (**$p < 0.001$**), indicating that a one dolar increase in fuel price is associated with a decrease of approximately **37.94** gallons per capita in fuel consumption, holding GDP per capita constant. The coefficient for **gdppc** is positive (**0.0035**) and also highly significant (**$p < 0.001$**), meaning that a **$1,000** increase in GDP per capita is associated with an increase of about **3.5** gallons per capita in fuel consumption, holding fuel price constant.

- The model explains **64.6%** of the variation in fuel consumption (**R-squared = 0.646**). The F-statistic is highly significant (**p = 1.71e-07**), confirming that the overall model is statistically valid.

- These results are consistent with economic theory. The negative price coefficient aligns with the law of demand, and the positive income coefficient reflects fuel as a normal good.

Log-Log Specification: **ln(fuelcon) = β0 + β1 * ln(fuelprice) + β2 * ln(gdppc) + ε**

- In this specification, the coefficients represent elasticities. Thus, the price elasticity of demand is **-1.18**. This means that a **1%** increase in fuel price leads to a **1.18%** decrease in fuel consumption, holding income constant. This value indicates that fuel demand is elastic (|elasticity| > 1) in OECD countries.

- The income elasticity of demand is **0.65**. This means that a **1%** increase in GDP per capita leads to a **0.65%** increase in fuel consumption, holding price constant. This suggests fuel is a normal good, but not a luxury good (elasticity < 1).

- The log-log model provides a better fit, explaining **79.4%** of the variation in the log of fuel consumption (**Adjusted R-squared = 0.780**). The F-statistic is also highly significant (**p = 5.11e-11**).

- The magnitudes of the elasticities are plausible. A price elasticity greater than 1 in absolute value is reasonable for motor fuels in developed economies, where consumers have more substitutes (public transport, fuel-efficient vehicles) and can adjust their behavior over time. An income elasticity less than 1 is also expected for a necessity like fuel in high-income countries.

2. Fuel Demand for Non-OECD Countries

In [6]:

```
# Create scatter plots for non-OECD countries
fig, axes = plt.subplots(1, 2, figsize=(15, 5))

# Plot 3: Fuel consumption vs Fuel price
axes[0].scatter(non_oecd_df['fuelprice'], non_oecd_df['fuelcon'], alpha=0.7)
axes[0].set_xlabel('Fuel Price ($/gallon)')
axes[0].set_ylabel('Fuel Consumption (gallons/capita)')
axes[0].set_title('Figure 3 - Non-OECD: Fuel Consumption vs Price')
axes[0].grid(True, alpha=0.3)

# Plot 4: Fuel consumption vs GDP per capita
axes[1].scatter(non_oecd_df['gdppc'], non_oecd_df['fuelcon'], alpha=0.7)
axes[1].set_xlabel('GDP per capita ($)')
axes[1].set_ylabel('Fuel Consumption (gallons/capita)')
axes[1].set_title('Figure 4 - Non-OECD: Fuel Consumption vs GDP per capita')
axes[1].grid(True, alpha=0.3)

plt.tight_layout()
plt.show()

# Regression analysis for non-OECD countries
# Linear specification
X_linear_non = non_oecd_df[['fuelprice', 'gdppc']]
X_linear_non = sm.add_constant(X_linear_non)
y_linear_non = non_oecd_df['fuelcon']

model_linear_non = sm.OLS(y_linear_non, X_linear_non).fit()

# Log specification
X_log_non = np.log(non_oecd_df[['fuelprice', 'gdppc']] + small_constant)
X_log_non = sm.add_constant(X_log_non)
y_log_non = np.log(non_oecd_df['fuelcon'] + small_constant)

model_log_non = sm.OLS(y_log_non, X_log_non).fit()

print("="*60)
print("Table 2 - NON-OECD COUNTRIES REGRESSION RESULTS")
print("="*60)

print("\nLINEAR SPECIFICATION:")
print(model_linear_non.summary())

print("\n\nLOG-LOG SPECIFICATION:")
print(model_log_non.summary())
```

Figure 3 - Non-OECD: Fuel Consumption vs Price

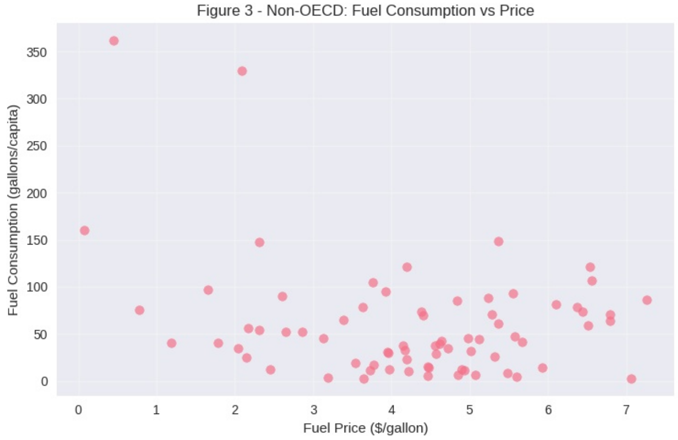
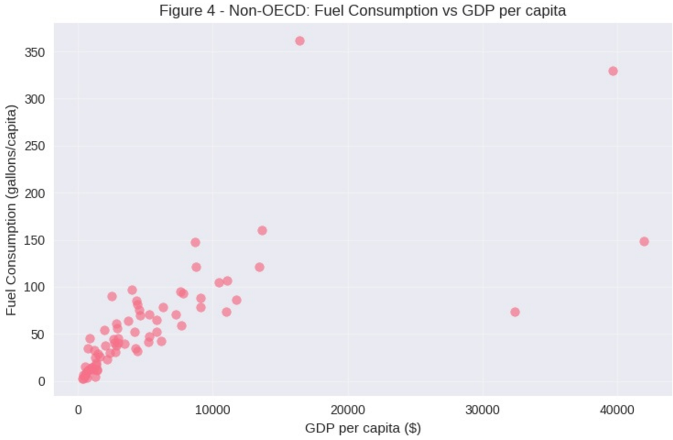


Figure 4 - Non-OECD: Fuel Consumption vs GDP per capita




```
============================================================
NON-OECD COUNTRIES REGRESSION RESULTS
============================================================

LINEAR SPECIFICATION:
                            OLS Regression Results
==============================================================================
Dep. Variable:                fuelcon   R-squared:                       0.605
Model:                            OLS   Adj. R-squared:                  0.594
Method:                 Least Squares   F-statistic:                     53.64
Date:                Fri, 26 Sep 2025   Prob (F-statistic):           7.52e-15
Time:                        15:35:13   Log-Likelihood:                -369.70
No. Observations:                  73   AIC:                             745.4
Df Residuals:                      70   BIC:                             752.3
Df Model:                           2
Covariance Type:            nonrobust
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
const         74.4555     13.313      5.593      0.000      47.904     101.007
fuelprice    -11.1182      2.849     -3.903      0.000     -16.800      -5.436
gdppc          0.0057      0.001      9.643      0.000       0.005       0.007
==============================================================================
Omnibus:                       40.942   Durbin-Watson:                   1.899
Prob(Omnibus):                  0.000   Jarque-Bera (JB):              277.801
Skew:                           1.346   Prob(JB):                     4.75e-61
Kurtosis:                      12.170   Cond. No.                     2.81e+04
==============================================================================

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
[2] The condition number is large, 2.81e+04. This might indicate that there are
strong multicollinearity or other numerical problems.


LOG-LOG SPECIFICATION:
                            OLS Regression Results
==============================================================================
Dep. Variable:                fuelcon   R-squared:                       0.814
Model:                            OLS   Adj. R-squared:                  0.808
Method:                 Least Squares   F-statistic:                     152.8
Date:                Fri, 26 Sep 2025   Prob (F-statistic):           2.92e-26
Time:                        15:35:13   Log-Likelihood:                -41.716
No. Observations:                  73   AIC:                             89.43
Df Residuals:                      70   BIC:                             96.30
Df Model:                           2
Covariance Type:            nonrobust
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
const         -1.8854      0.449     -4.200      0.000      -2.781      -0.990
fuelprice     -0.3938      0.133     -2.972      0.004      -0.658      -0.130
gdppc          0.7725      0.046     16.762      0.000       0.681       0.864
==============================================================================
Omnibus:                        1.158   Durbin-Watson:                   1.769
Prob(Omnibus):                  0.560   Jarque-Bera (JB):                0.573
Skew:                          -0.119   Prob(JB):                        0.751
Kurtosis:                       3.363   Cond. No.                         74.0
==============================================================================

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

DISCUSSION OF PART 2:

I continued the analysis restricting the dataset to Non-OECD countries (n = 73).

Then, I generated the two scatter plots to visualize the relationships:

- The scatter plot in **Figure 3** shows a negative relationship, though it appears weaker and more dispersed than in OECD countries. Higher fuel prices are generally associated with lower per capita fuel consumption, but there is considerable variation, likely due to differences in subsidies, infrastructure, and economic development.
- A strong positive relationship is evident from **Figure 4**. As GDP per capita rises, fuel consumption per capita also increases, often more steeply at lower income levels. This suggests that in developing economies, rising income significantly boosts access to vehicles and energy use.

Regression Analysis Results: I estimated both the linear and log-log regression models for non-OECD countries and they are shown in **Table 2**.

Linear Specification: fuelcon = $\beta_0 + \beta_1$·fuelprice + β_2·gdppc + ε

- A one dolar increase in fuel price is associated with a **11.12-gallon** decrease in per capita fuel consumption, holding income constant. A **$1,000** increase in GDP per capita is associated with a **5.7-gallon** increase in fuel consumption.
- The model explains **60.5%** of the variation in fuel consumption (**R^2 = 0.605**). The F-statistic is highly significant (**$p < 0.001$**).
- The model shows signs of non-normality (**Jarque-Bera p ≈ 0**, high kurtosis and positive skew), suggesting the linear model may not fully capture the data structure, possibly due to heterogeneity across diverse non-OECD economies.

Log-Log Specification: ln(fuelcon) = $\beta_0 + \beta_1$·ln(fuelprice) + β_2·ln(gdppc) + ε

- The price elasticity of **–0.39** indicates that a **1%** increase in fuel price leads to a **0.39%** decrease in fuel consumption. This indicates inelastic demand in non-OECD countries, where consumers are less responsive to price changes, possibly due to limited alternatives (e.g., poor public transport) or fuel subsidies.
- The income elasticity of *0.77** suggests that a **1%** increase in GDP per capita raises fuel consumption by **0.77%**, confirming fuel as a normal good. The elasticity is slightly higher than in OECD countries (**0.65**), suggesting income plays a relatively larger role in driving fuel use in developing economies.
- In terms of goodness of fit, the log-log model fits better, with **R^2 = 0.814** and well-behaved residuals (**Jarque-Bera p = 0.751, indicating normality**).
- Regarding the consistencies with the expectations, I see that the lower price elasticity aligns with economic intuition for lower-income countries where fuel may be essential for basic mobility and less substitutable. The positive and substantial income elasticity reflects the strong link between development and motorization.

Comparison with OECD Results:

- For context, even though not required in this part of the assignment, I think that it is worth noting that the price elasticity in non-OECD countries (**–0.39**) is much smaller in magnitude than in OECD countries (**–1.18**), which may confirm that consumers in wealthier nations are more sensitive to fuel prices, likely due to better access to alternatives and higher baseline consumption.

3. Additional Factors Analysis

In [4]:

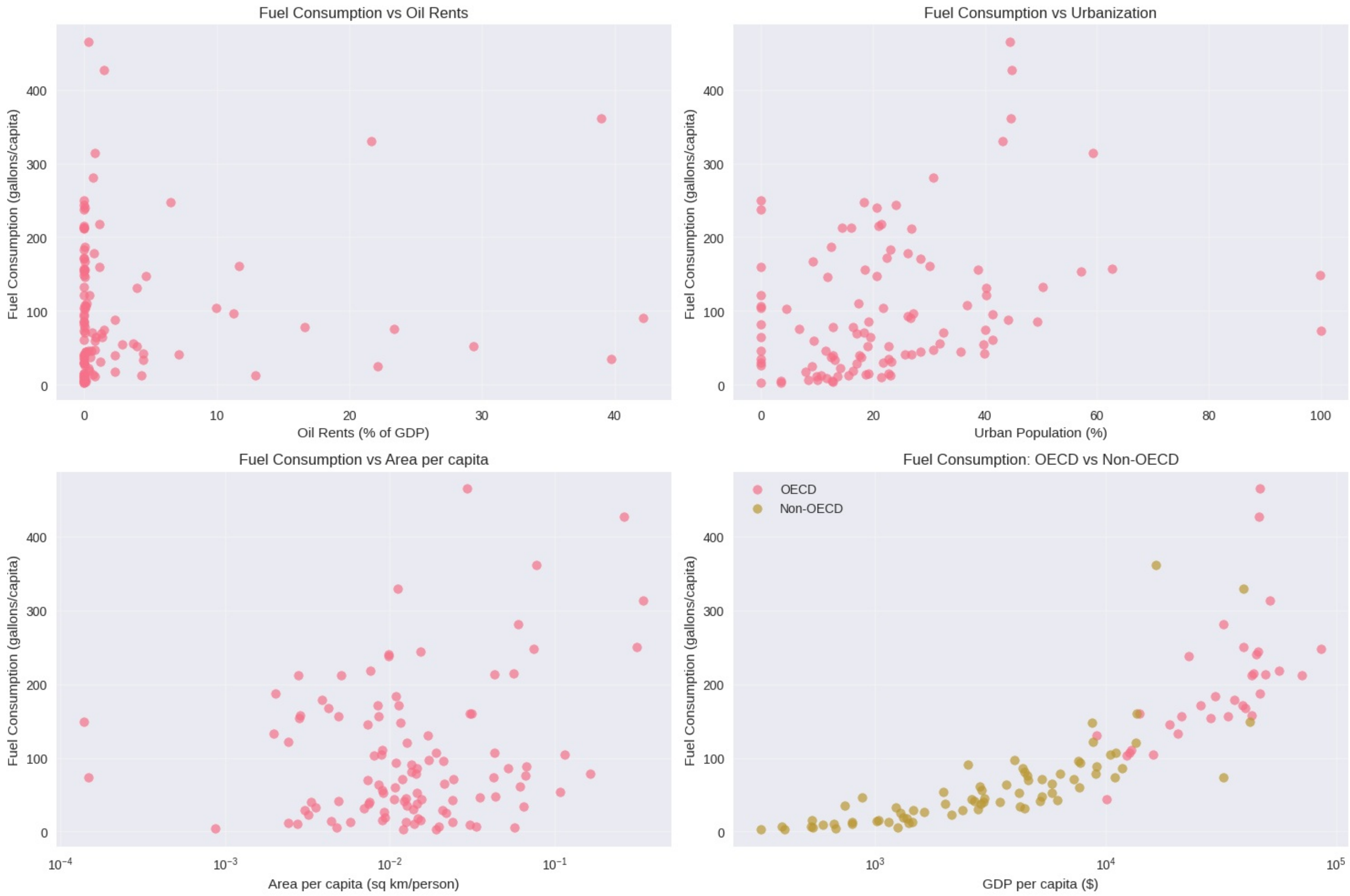
```
# Create new variables
df['area_per_capita'] = df['area'] / df['pop']
df['log_area_per_capita'] = np.log(df['area_per_capita'] + small_constant)

# Prepare data for comprehensive analysis
df_clean = df.dropna(subset=['fuelcon', 'fuelprice', 'gdppc', 'oil_rents_gdp', 'pop_urban', 'area_per_capita'])

# Log transformations for comprehensive analysis
df_clean['log_fuelcon'] = np.log(df_clean['fuelcon'] + small_constant)
df_clean['log_fuelprice'] = np.log(df_clean['fuelprice'] + small_constant)
df_clean['log_gdppc'] = np.log(df_clean['gdppc'] + small_constant)
df_clean['log_oil_rents'] = np.log(df_clean['oil_rents_gdp'] + small_constant)

print(f"Countries available for comprehensive analysis: {len(df_clean)}")

# Comprehensive regression including skeptic's factors
formula = 'log_fuelcon ~ log_fuelprice + log_gdppc + oil_rents_gdp + pop_urban + log_area_per_capita'
model_comprehensive = smf.ols(formula, data=df_clean).fit()

print("COMPREHENSIVE REGRESSION RESULTS")
print("="*50)
print(model_comprehensive.summary())

# Separate analyses for OECD and non-OECD
formula_oecd = 'log_fuelcon ~ log_fuelprice + log_gdppc + oil_rents_gdp + pop_urban + log_area_per_capita'
```

```python
model_oecd_comp = smf.ols(formula_oecd, data=df_clean[df_clean['oecd'] == 1]).fit()

model_non_oecd_comp = smf.ols(formula_oecd, data=df_clean[df_clean['oecd'] == 0]).fit()

print("Table 3 - OECD COMPREHENSIVE REGRESSION:")
print(model_oecd_comp.summary())

print("\n\n Table 4 - NON-OECD COMPREHENSIVE REGRESSION:")
print(model_non_oecd_comp.summary())

# Create visualizations for additional factors
fig, axes = plt.subplots(2, 2, figsize=(15, 10))

# Oil rents vs fuel consumption
axes[0,0].scatter(df_clean['oil_rents_gdp'], df_clean['fuelcon'], alpha=0.7)
axes[0,0].set_xlabel('Oil Rents (% of GDP)')
axes[0,0].set_ylabel('Fuel Consumption (gallons/capita)')
axes[0,0].set_title('Figure 5 - Fuel Consumption vs Oil Rents')
axes[0,0].grid(True, alpha=0.3)

# Urban population vs fuel consumption
axes[0,1].scatter(df_clean['pop_urban'], df_clean['fuelcon'], alpha=0.7)
axes[0,1].set_xlabel('Urban Population (%)')
axes[0,1].set_ylabel('Fuel Consumption (gallons/capita)')
axes[0,1].set_title('Figure 6 - Fuel Consumption vs Urbanization')
axes[0,1].grid(True, alpha=0.3)

# Area per capita vs fuel consumption
axes[1,0].scatter(df_clean['area_per_capita'], df_clean['fuelcon'], alpha=0.7)
axes[1,0].set_xlabel('Area per capita (sq km/person)')
axes[1,0].set_ylabel('Fuel Consumption (gallons/capita)')
axes[1,0].set_title('Figure 7 - Fuel Consumption vs Area per capita')
axes[1,0].set_xscale('log')
axes[1,0].grid(True, alpha=0.3)

# OECD vs non-OECD comparison
for i, (label, data) in enumerate([('OECD', oecd_df), ('Non-OECD', non_oecd_df)]):
    axes[1,1].scatter(data['gdppc'], data['fuelcon'], alpha=0.7, label=label)
axes[1,1].set_xlabel('GDP per capita ($)')
axes[1,1].set_ylabel('Fuel Consumption (gallons/capita)')
axes[1,1].set_title('Comparison of Fuel Consumption: OECD vs Non-OECD')
axes[1,1].legend()
axes[1,1].set_xscale('log')
axes[1,1].grid(True, alpha=0.3)

plt.tight_layout()
plt.show()

# Confidence interval comparison function
def compare_coefficients(model1, model2, var_names, model1_name="Model 1", model2_name="Model 2"):
    """Compare coefficients and confidence intervals between two models"""
    comparison = []
    for var in var_names:
        if var in model1.params.index and var in model2.params.index:
            coef1 = model1.params[var]
            ci1 = model1.conf_int().loc[var]
            coef2 = model2.params[var]
            ci2 = model2.conf_int().loc[var]

            comparison.append({
                'Variable': var,
                f'{model1_name}_Coef': coef1,
                f'{model1_name}_CI_Lower': ci1[0],
                f'{model1_name}_CI_Upper': ci1[1],
                f'{model2_name}_Coef': coef2,
                f'{model2_name}_CI_Lower': ci2[0],
                f'{model2_name}_CI_Upper': ci2[1],
                'Overlap': (ci1[0] <= ci2[1]) and (ci2[0] <= ci1[1])
            })

    return pd.DataFrame(comparison)

# Compare OECD vs non-OECD coefficients
var_comparison = compare_coefficients(model_log, model_log_non,
                                     ['const', 'log_fuelprice', 'log_gdppc'],
                                     "OECD", "Non-OECD")
print("COEFFICIENT COMPARISON: OECD vs NON-OECD")
print("="*50)
print(var_comparison)
```

```
Countries available for comprehensive analysis: 106
COMPREHENSIVE REGRESSION RESULTS
==================================================
                            OLS Regression Results
```

```
==============================================================================
Dep. Variable:            log_fuelcon   R-squared:                       0.887
Model:                            OLS   Adj. R-squared:                  0.881
Method:                 Least Squares   F-statistic:                     156.7
Date:                Fri, 26 Sep 2025   Prob (F-statistic):           1.13e-45
Time:                        14:47:19   Log-Likelihood:                -46.231
No. Observations:                 106   AIC:                             104.5
Df Residuals:                     100   BIC:                             120.4
Df Model:                           5
Covariance Type:            nonrobust
=======================================================================================
                          coef    std err          t      P>|t|      [0.025      0.975]
---------------------------------------------------------------------------------------
Intercept              -1.6301      0.268     -6.085      0.000      -2.162      -1.099
log_fuelprice          -0.5179      0.135     -3.842      0.000      -0.785      -0.250
log_gdppc               0.7743      0.033     23.605      0.000       0.709       0.839
oil_rents_gdp          -0.0016      0.006     -0.257      0.798      -0.014       0.010
pop_urban              -0.0043      0.002     -1.843      0.068      -0.009       0.000
log_area_per_capita     0.9233      0.806      1.146      0.255      -0.676       2.522
==============================================================================
Omnibus:                        2.014   Durbin-Watson:                   1.931
Prob(Omnibus):                  0.365   Jarque-Bera (JB):                1.580
Skew:                          -0.082   Prob(JB):                        0.454
Kurtosis:                       3.575   Cond. No.                         645.
==============================================================================

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
OECD COMPREHENSIVE REGRESSION:
                            OLS Regression Results
==============================================================================
Dep. Variable:            log_fuelcon   R-squared:                       0.841
Model:                            OLS   Adj. R-squared:                  0.812
Method:                 Least Squares   F-statistic:                     28.66
Date:                Fri, 26 Sep 2025   Prob (F-statistic):           5.34e-10
Time:                        14:47:19   Log-Likelihood:                 11.389
No. Observations:                  33   AIC:                            -10.78
Df Residuals:                      27   BIC:                            -1.798
Df Model:                           5
Covariance Type:            nonrobust
=======================================================================================
                          coef    std err          t      P>|t|      [0.025      0.975]
---------------------------------------------------------------------------------------
Intercept               1.2395      0.652      1.902      0.068      -0.098       2.577
log_fuelprice          -1.2619      0.212     -5.949      0.000      -1.697      -0.827
log_gdppc               0.6447      0.065      9.966      0.000       0.512       0.777
oil_rents_gdp          -0.0199      0.026     -0.757      0.455      -0.074       0.034
pop_urban              -0.0044      0.002     -2.112      0.044      -0.009      -0.000
log_area_per_capita     0.9073      0.479      1.894      0.069      -0.076       1.890
==============================================================================
Omnibus:                        1.154   Durbin-Watson:                   2.207
Prob(Omnibus):                  0.562   Jarque-Bera (JB):                0.886
Skew:                          -0.006   Prob(JB):                        0.642
Kurtosis:                       2.197   Cond. No.                         640.
==============================================================================

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


NON-OECD COMPREHENSIVE REGRESSION:
                            OLS Regression Results
==============================================================================
Dep. Variable:            log_fuelcon   R-squared:                       0.827
Model:                            OLS   Adj. R-squared:                  0.814
Method:                 Least Squares   F-statistic:                     63.98
Date:                Fri, 26 Sep 2025   Prob (F-statistic):           3.60e-24
Time:                        14:47:19   Log-Likelihood:                -39.028
No. Observations:                  73   AIC:                             90.06
Df Residuals:                      67   BIC:                             103.8
Df Model:                           5
Covariance Type:            nonrobust
=======================================================================================
                          coef    std err          t      P>|t|      [0.025      0.975]
---------------------------------------------------------------------------------------
Intercept              -2.3601      0.498     -4.735      0.000      -3.355      -1.365
log_fuelprice          -0.3641      0.168     -2.171      0.033      -0.699      -0.029
log_gdppc               0.8439      0.059     14.424      0.000       0.727       0.961
oil_rents_gdp           0.0012      0.007      0.161      0.873      -0.013       0.015
pop_urban              -0.0076      0.003     -2.202      0.031      -0.015      -0.001
log_area_per_capita     0.5853      2.001      0.292      0.771      -3.409       4.580
==============================================================================
Omnibus:                        0.626   Durbin-Watson:                   1.761
```

```
Prob(Omnibus):                  0.731   Jarque-Bera (JB):                0.196
Skew:                           0.064   Prob(JB):                        0.907
Kurtosis:                       3.219   Cond. No.                     1.16e+03
==============================================================================

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
[2] The condition number is large, 1.16e+03. This might indicate that there are
strong multicollinearity or other numerical problems.
```




```
COEFFICIENT COMPARISON: OECD vs NON-OECD
==================================================
  Variable  OECD_Coef  OECD_CI_Lower  OECD_CI_Upper  Non-OECD_Coef  \
0    const   0.876241      -0.532532       2.285013      -1.885366

   Non-OECD_CI_Lower  Non-OECD_CI_Upper  Overlap
0          -2.780672           -0.99006    False
```

DISCUSSION OF PART 3:

A. Examining the additional factors that I think may influence fuel demand:

- Oil rents (% of GDP)
- Urban population (% of total population)
- Area per capita (as a proxy for population density or geographic dispersion)

My analysis, therefore, included a regression model using the full sample (106 countries), as well as separate models for OECD and non-OECD countries, all in log-log form (with some variables in levels). I generated three scatter plots for each of the factors to explore potential relationships:

- Regarding the fuel consumption vs. oil rents (% of GDP), I see no clear linear pattern. High oil rents (e.g., in oil-exporting nations) do not consistently correspond to higher or lower fuel consumption, suggesting that oil wealth may not directly translate into domestic fuel use, possibly due to pricing policies or subsidies.

- Regarding the fuel consumption vs. urban population (%), I noticed that a moderate positive relationship appears, especially among non-OECD countries. Urbanization may increase fuel demand due to congestion, commuting, and economic activity, though in some high-income cities, public transport may offset this effect.

- Finally, regarding fuel consumption vs. area per capita (log scale), a positive association is visible, where countries with more land per person (e.g., Canada, Australia, Kazakhstan) tend to have higher fuel consumption, likely due to longer travel distances and car dependency.

B. A log-log regression model was estimated using all 106 countries and the proposed model was:

$\ln(fuelcon) = \beta_0 + \beta_1 \cdot \ln(fuelprice) + \beta_2 \cdot \ln(gdppc) + \beta_3 \cdot oil\_rents\_gdp + \beta_4 \cdot pop\_urban +$

$\beta_5 \cdot \ln(\text{area\_per\_capita}) + \varepsilon$

- In terms of goodness of fit, the model explains **88.7%** of the variation in log fuel consumption (**$R^2 = 0.887$**), a substantial improvement over the basic two-variable model.
- Despite theoretical relevance, oil rents and area per capita are not statistically significant in the full sample. Urbanization is marginally significant (**$p = 0.068$**) with a negative sign, which is contrary to initial visual impression.

C. Separate Analyses: OECD vs. Non-OECD: To assess heterogeneity, I ran the model separately for each group and my interpretations were as follows:

- **Regarding OECD Countries:**
  - **ln(fuelprice)** coefficient: **–1.262** (**$p < 0.001$**) (highly elastic demand).
  - **pop_urban** is negative and significant (**$p = 0.044$**): in developed countries, more urbanization is associated with lower per capita fuel consumption, likely due to efficient public transport and compact cities.
  - **oil_rents_gdp** and **ln(area_per_capita)** remain insignificant.
- **Regarding Non-OECD Countries:**
  - **ln(fuelprice)** coefficient: **–0.364** (**$p = 0.033$**) (inelastic demand, consistent with what I observed from Part 2).
  - **pop_urban** is negative and significant (**$p = 0.031$**): even in developing countries, urbanization correlates with lower per capita fuel use, possibly because rural populations rely on fuel for generators, agriculture, or lack alternatives.
  - **oil_rents_gdp** is positive but insignificant (**$p = 0.873$**), suggesting oil wealth does not systematically increase domestic fuel consumption (perhaps due to export orientation or subsidies that don’t raise consumption).
  - **ln(area_per_capita)** is insignificant (**$p = 0.771$**), with a very large standard error.

D. Do the “Skeptic’s Factors” Matter?

- I believe this likely refers to potential omitted variables that a skeptic might argue drive fuel demand more than price or income (e.g., geography, oil wealth, urban structure).
  - **Oil rents**: Not significant in any specification. This suggests that being an oil-rich country does not lead to systematically higher domestic fuel consumption, i.e., policy (e.g., subsidies or taxes) likely mediates this relationship.
  - **Urbanization**: Consistently negative and significant in both subgroups. This challenges the naive view that cities increase fuel use; instead, they appear to reduce per capita consumption, supporting the role of density and public transit.
  - **Area per capita**: While intuitively plausible, it lacks statistical significance, possibly because its effect is already captured by income and urbanization, or because the measure is noisy.

E. Conclusions for Part 3:

- What I can conclude from this is that the inclusion of additional factors improves model fit but does not overturn the core findings from Parts 1 and 2. That is, price and income remain the dominant and statistically robust determinants of fuel demand, as well as urbanization has a significant negative effect, reinforcing that city design influences consumption.
- Also, oil rents and country size (area per capita) do not emerge as key drivers in this dataset.
- Therefore, I think that my original original conclusions about price and income elasticities are robust to the inclusion of these additional variables.