Marketing Campaign Data Analysis

December 12, 2024

1 ARM

1.1 Libs

[11]:
```
import pandas as pd
import matplotlib.pyplot as plt
import numpy as np
import seaborn as sns
from sklearn.linear_model import LinearRegression
from sklearn import metrics
from sklearn.metrics import mean_squared_error
from sklearn.metrics import r2_score
from sklearn.model_selection import cross_val_score
from sklearn.model_selection import cross_val_predict
from sklearn.model_selection import KFold
from sklearn.model_selection import train_test_split
import statsmodels.api as sm
from statsmodels.formula.api import ols
import statsmodels.formula.api as smf
from statsmodels.graphics.api import plot_regress_exog

# No Perfect Multicollinearity: Variance Inflation Factor (VIF)
from statsmodels.stats.outliers_influence import variance_inflation_factor

from statsmodels.stats.diagnostic import het_breuschpagan
from scipy.stats import shapiro
from statsmodels.stats.stattools import durbin_watson
```

1.2 Intro

[12]:
```
df = pd.read_excel('marketing_campaign.xlsx')
df_sub = df.sample(100)
df_sub.head()
```

[12]:
```
        ID  Year_Birth   Education Marital_Status   Income  Kidhome  Teenhome  \
Dt_Customer  Recency  MntWines  MntFruits  MntMeatProducts  MntFishProducts  \
MntSweetProducts  MntGoldProds  NumDealsPurchases  NumWebPurchases  \
NumCatalogPurchases  NumStorePurchases  NumWebVisitsMonth  AcceptedCmp3  \
```

```
AcceptedCmp4  AcceptedCmp5  AcceptedCmp1  AcceptedCmp2  Complain  Z_CostContact
Z_Revenue  Response
781  10839        1976  Graduation       Together  36283.0        1          1
2014-04-14        42         6          5                5                8
0             5                   2                1                   0
3                 4             0             0             0             0
0          0              3         11          0
857    425        1985  Graduation        Married  55357.0        2          0
2013-02-19        66       374         64              116               84
25            64                   3                6                   2
11                5             0             0             0             0
0          0              3         11          0
564  10232        1963         PhD       Divorced  48799.0        0          1
2013-11-05         9       174         18               81               28
6            24                   3                3                   2
7                 3             0             0             0             0
0          0              3         11          0
60    6853        1982      Master         Single  75777.0        0          0
2013-07-04        12       712         26              538               69
13            80                   1                3                   6
11                1             0             1             1             0
0          0              3         11          1
341  11191        1986  Graduation       Divorced  41411.0        0          0
2013-12-07        11        37         32               38               11
3            18                   1                2                   1
4                 6             0             0             0             0
0          0              3         11          0
```

[13]:
```
df_sub.describe().T
```

[13]:
```
                     count                 mean                  min
25%                  50%                  75%                  max          std
ID                   100.0              6243.75                 17.0
3693.5               6513.0               9415.75              11191.0
3253.59886
Year_Birth           100.0              1970.11               1945.0
1959.0               1971.0               1980.0               1995.0
12.453465
Income                99.0          50812.30303              13084.0
35868.0              49912.0              65257.5              94472.0
19470.632651
Kidhome              100.0                 0.43                  0.0
0.0                  0.0                  1.0                  2.0       0.536637
Teenhome             100.0                 0.57                  0.0
0.0                  1.0                  1.0                  2.0       0.590412
Dt_Customer            100  2013-08-30 20:24:00  2012-08-07 00:00:00  2013-04-30
12:00:00  2013-09-17 12:00:00  2014-01-30 18:00:00  2014-06-22 00:00:00
```

```
NaN
Recency             100.0            45.89            0.0
20.0                42.5            70.25            99.0
28.965983
MntWines            100.0           289.63            0.0
22.75               210.0            436.5          1103.0
299.032773
MntFruits           100.0            26.48            0.0
1.0                 8.0             34.25          172.0    38.776615
MntMeatProducts     100.0           147.13            2.0
11.0                68.5            216.25          804.0
186.777275
MntFishProducts     100.0            35.39            0.0
3.0                15.0             43.25          220.0     51.98502
MntSweetProducts    100.0            26.23            0.0
1.75                 7.5             32.5           197.0
38.731621
MntGoldProds        100.0            38.14            0.0
9.0                20.0             50.25          218.0    43.613319
NumDealsPurchases   100.0             2.25            0.0
1.0                 2.0              3.0            10.0     1.816729
NumWebPurchases     100.0             3.86            0.0
2.0                 3.5              6.0            11.0     2.534689
NumCatalogPurchases 100.0             2.72            0.0
0.0                 2.0              5.0            11.0     2.913154
NumStorePurchases   100.0             5.78            2.0
3.0                 5.0              8.0            13.0     3.192732
NumWebVisitsMonth   100.0             5.19            1.0
3.0                 5.0              7.0            10.0     2.149442
AcceptedCmp3        100.0             0.08            0.0
0.0                 0.0              0.0             1.0      0.27266
AcceptedCmp4        100.0             0.07            0.0
0.0                 0.0              0.0             1.0     0.256432
AcceptedCmp5        100.0             0.05            0.0
0.0                 0.0              0.0             1.0     0.219043
AcceptedCmp1        100.0             0.05            0.0
0.0                 0.0              0.0             1.0     0.219043
AcceptedCmp2        100.0             0.02            0.0
0.0                 0.0              0.0             1.0     0.140705
Complain            100.0             0.01            0.0
0.0                 0.0              0.0             1.0          0.1
Z_CostContact       100.0              3.0            3.0
3.0                 3.0              3.0             3.0          0.0
Z_Revenue           100.0             11.0           11.0
11.0                11.0             11.0           11.0
0.0
Response            100.0              0.1            0.0
```

```
0.0                    0.0                    0.0                    1.0       0.301511
```

[14]:
```
df_sub.dtypes
```

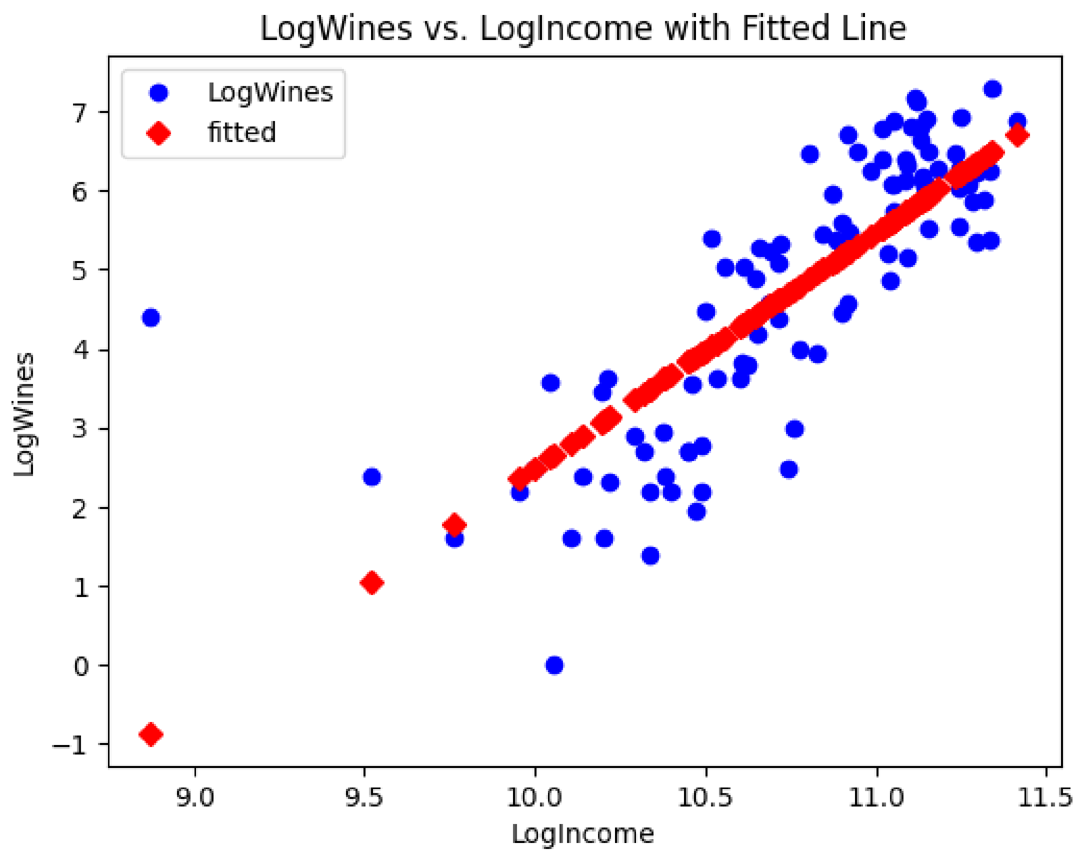
[14]:
```
ID                                int64
Year_Birth                        int64
Education                        object
Marital_Status                   object
Income                          float64
Kidhome                           int64
Teenhome                          int64
Dt_Customer              datetime64[ns]
Recency                           int64
MntWines                          int64
MntFruits                         int64
MntMeatProducts                   int64
MntFishProducts                   int64
MntSweetProducts                  int64
MntGoldProds                      int64
NumDealsPurchases                 int64
NumWebPurchases                   int64
NumCatalogPurchases               int64
NumStorePurchases                 int64
NumWebVisitsMonth                 int64
AcceptedCmp3                      int64
AcceptedCmp4                      int64
AcceptedCmp5                      int64
AcceptedCmp1                      int64
AcceptedCmp2                      int64
Complain                          int64
Z_CostContact                     int64
Z_Revenue                         int64
Response                          int64
dtype: object
```

1.3 H1

[21]:
```
# Charger le dataset
file_path = 'marketing_campaign.xlsx'
data = pd.read_excel(file_path)

# Échantillonner et nettoyer les données
data_sub = data.sample(100)
data_sub = data_sub.dropna(subset=['MntWines', 'Income'])  # Retirer les␣
 ↪valeurs manquantes

# Filtrer les données pour exclure les revenus supérieurs à 100000
```

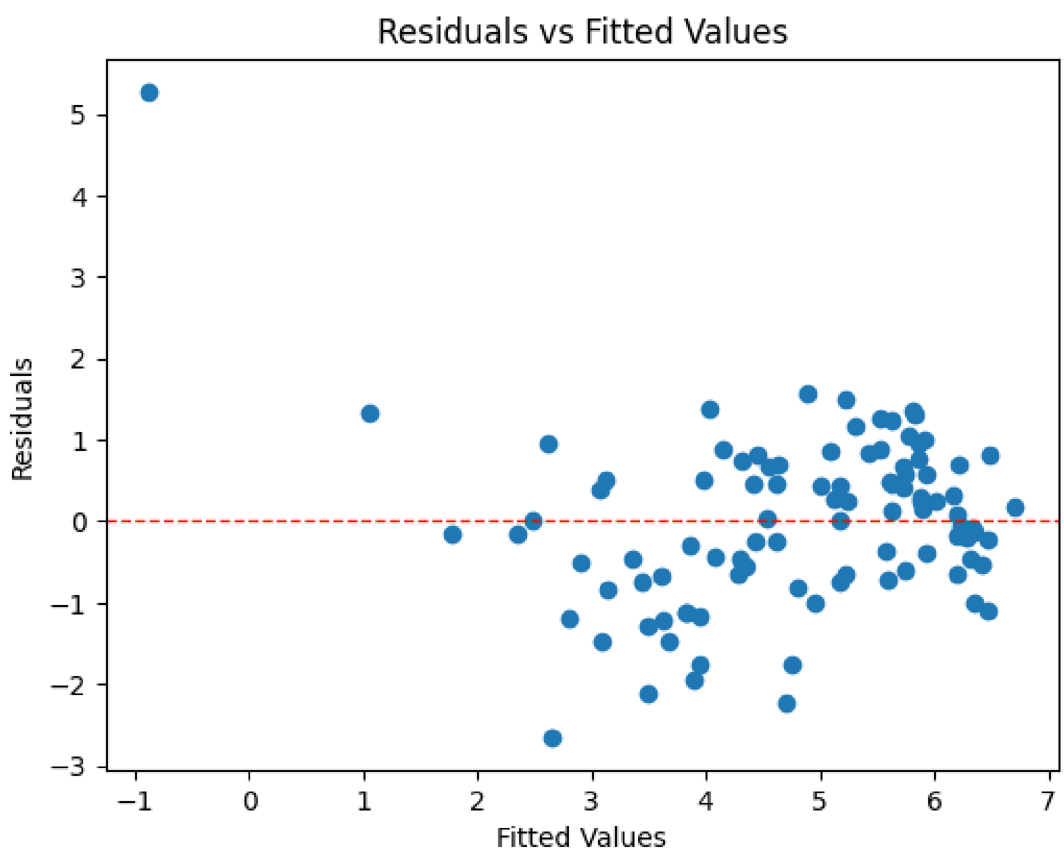
```
data_sub = data_sub[data_sub['Income'] <= 100000]

data_sub['LogIncome'] = np.log(data_sub['Income'])
data_sub['LogWines'] = np.log(data_sub['MntWines'] + 1)  # Add 1 to avoid log(0)

# Créer le modèle de régression avec LogIncome
model_h1 = ols("LogWines ~ LogIncome", data=data_sub).fit()

# Générer le graphe "Y and Fitted vs. X" uniquement
fig = sm.graphics.plot_fit(model_h1, "LogIncome", vlines=False)  # vlines=False␣
↪pour éviter les lignes verticales

plt.title("LogWines vs. LogIncome with Fitted Line")
plt.xlabel("LogIncome")
plt.ylabel("LogWines")
plt.show()

print(model_h1.summary())

# Describe
data_sub[['MntWines', 'Income']].describe().T

# ----------- OLS Assumption Checks ----------- #

# 1. Linearity: Residuals vs Fitted Plot
plt.scatter(model_h1.fittedvalues, model_h1.resid)
plt.axhline(0, color='red', linestyle='--', linewidth=1)
plt.title("Residuals vs Fitted Values")
plt.xlabel("Fitted Values")
plt.ylabel("Residuals")
plt.show()


# Create dataframe with only the independent variable(s)
x_vars = model_h1.model.exog
vif = pd.DataFrame()
vif["Variable"] = ["Intercept", "LogIncome"]
vif["VIF"] = [variance_inflation_factor(x_vars, i) for i in range(x_vars.
↪shape[1])]
print(vif)

# 3. Homoskedasticity: Breusch-Pagan Test
bp_test = het_breuschpagan(model_h1.resid, model_h1.model.exog)
print(f"Breusch-Pagan Test p-value: {bp_test[1]}")  # Second value is the␣
↪p-value

# 4. Zero Conditional Mean: Residuals centered around 0
```

```
plt.hist(model_h1.resid, bins=30, edgecolor='black')
plt.title("Distribution of Residuals")
plt.xlabel("Residuals")
plt.ylabel("Frequency")
plt.axvline(0, color='red', linestyle='--', linewidth=1)
plt.show()

# 5. Normality of Residuals: Shapiro-Wilk Test
shapiro_test = shapiro(model_h1.resid)
print(f"Shapiro-Wilk Test p-value: {shapiro_test.pvalue}")

# 6. Independence of Errors: Durbin-Watson Test
dw_stat = durbin_watson(model_h1.resid)
print(f"Durbin-Watson Statistic: {dw_stat}")
```

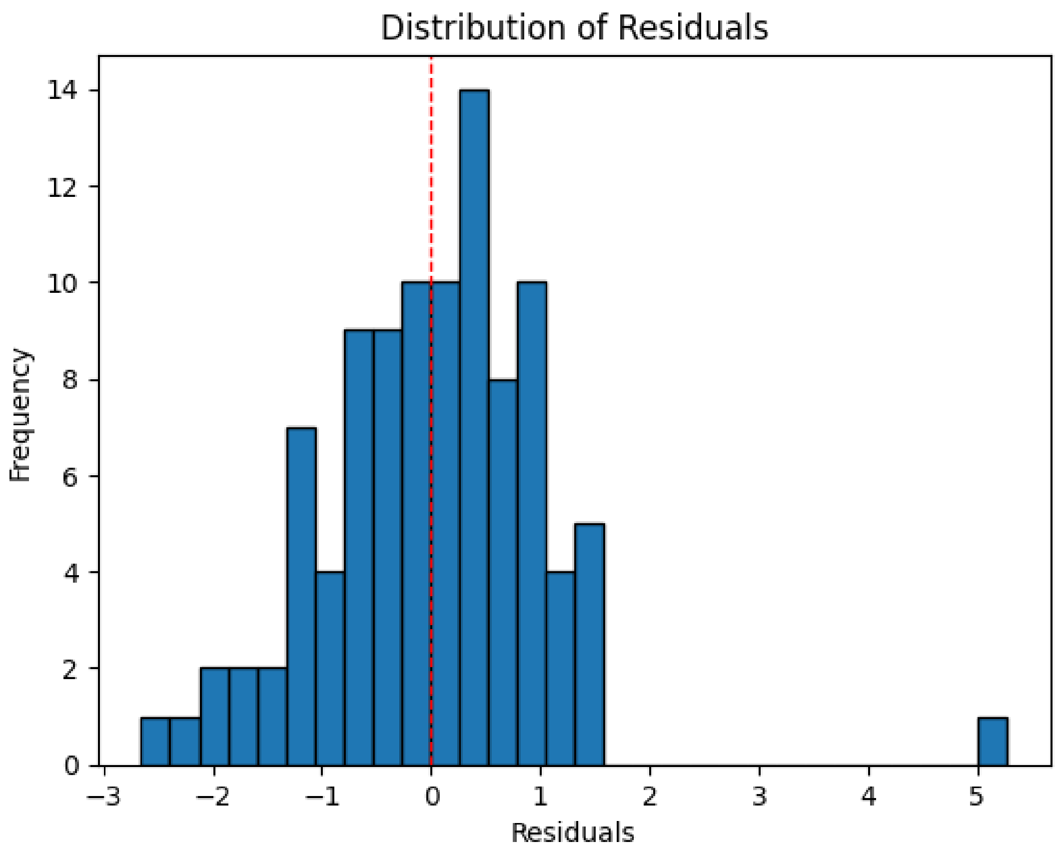



```
                            OLS Regression Results
==============================================================================
Dep. Variable:               LogWines   R-squared:                       0.622
Model:                            OLS   Adj. R-squared:                  0.618
Method:                 Least Squares   F-statistic:                     159.8
```

```
Date:                Wed, 11 Dec 2024   Prob (F-statistic):           3.17e-22
Time:                        17:08:42   Log-Likelihood:                -145.12
No. Observations:                  99   AIC:                             294.2
Df Residuals:                      97   BIC:                             299.4
Df Model:                           1
Covariance Type:            nonrobust
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
Intercept    -27.3257      2.543    -10.744      0.000     -32.373     -22.278
LogIncome      2.9813      0.236     12.641      0.000       2.513       3.449
==============================================================================
Omnibus:                       30.168   Durbin-Watson:                   1.521
Prob(Omnibus):                  0.000   Jarque-Bera (JB):              120.774
Skew:                           0.868   Prob(JB):                     5.95e-27
Kurtosis:                       8.125   Cond. No.                         260.
==============================================================================

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



```
    Variable          VIF
0  Intercept  571.197873
1  LogIncome    1.000000
Breusch-Pagan Test p-value: 7.275275757130443e-07
```




```
Shapiro-Wilk Test p-value: 3.5735220414094185e-05
Durbin-Watson Statistic: 1.5213796613004464
```

1.4 H2

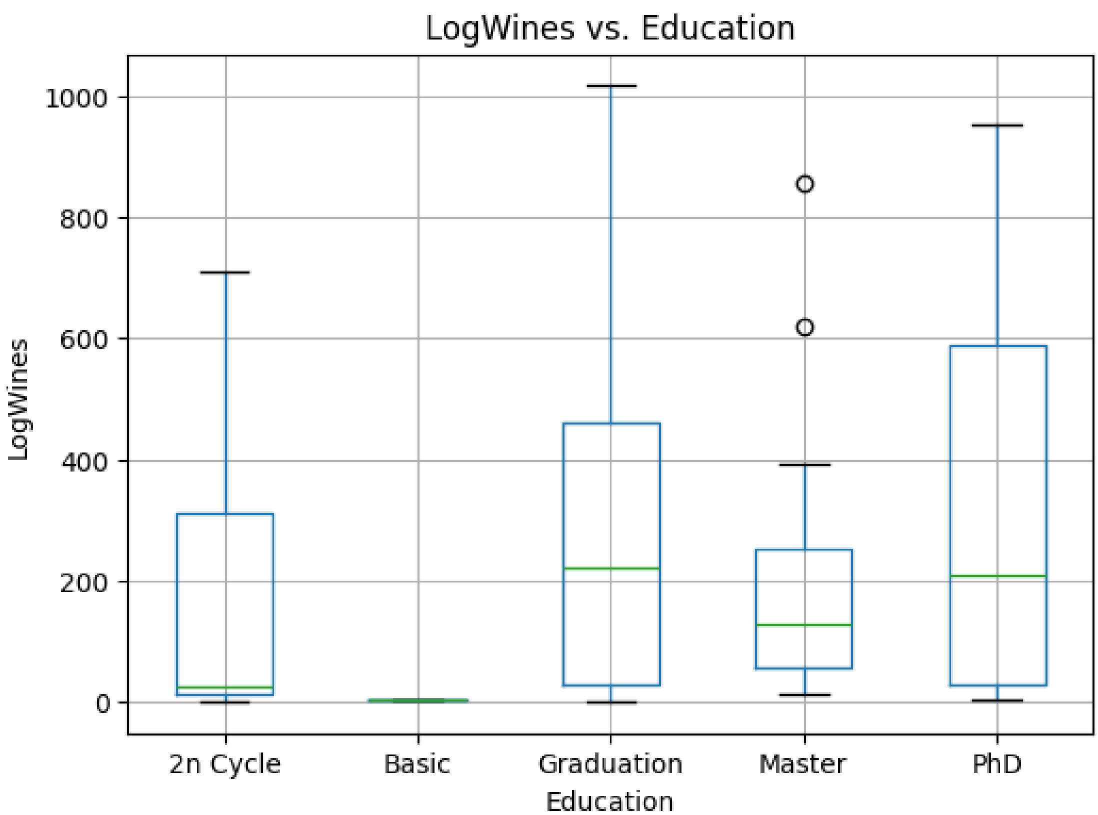
[17]:
```
import statsmodels.formula.api as smf
from statsmodels.graphics.api import plot_regress_exog
from statsmodels.stats.diagnostic import het_breuschpagan
from statsmodels.stats.stattools import durbin_watson
from scipy.stats import shapiro
import matplotlib.pyplot as plt

# Hypothesis 2: Categorical Variable
model_h2 = smf.ols("LogWines ~ C(Education)", data=data_sub).fit()
```

```python
print(model_h2.summary())

# Générer le graphe "Y and Fitted vs. X" uniquement
fig, ax = plt.subplots()
data_sub.boxplot(column='MntWines', by='Education', ax=ax)
plt.title("LogWines vs. Education")
plt.suptitle('')  # Suppress the default title
plt.xlabel("Education")
plt.ylabel("LogWines")

# Afficher le graphe
plt.show()

print(model_h2.summary())
data_sub[['LogWines','Education']].describe().T

# ----------- OLS Assumption Checks ----------- #

# 1. Linearity: Residuals vs Fitted Plot
plt.scatter(model_h2.fittedvalues, model_h2.resid)
plt.axhline(0, color='red', linestyle='--', linewidth=1)
plt.title("Residuals vs Fitted Values")
plt.xlabel("Fitted Values")
plt.ylabel("Residuals")
plt.show()

# 2. No Perfect Multicollinearity: Check Dummy Variables
# Print the dummy variable matrix
print(model_h2.model.exog[:5])

# 3. Homoskedasticity: Breusch-Pagan Test
bp_test = het_breuschpagan(model_h2.resid, model_h2.model.exog)
print(f"Breusch-Pagan Test p-value: {bp_test[1]}")  # Second value is the␣
↪p-value

# 4. Normality of Residuals: Shapiro-Wilk Test
shapiro_test = shapiro(model_h2.resid)
print(f"Shapiro-Wilk Test p-value: {shapiro_test.pvalue}")

# Plot the distribution of residuals
plt.hist(model_h2.resid, bins=30, edgecolor='black')
plt.title("Distribution of Residuals")
plt.xlabel("Residuals")
plt.ylabel("Frequency")
plt.axvline(0, color='red', linestyle='--', linewidth=1)
plt.show()
```

```python
# 5. Independence of Errors: Durbin-Watson Test
dw_stat = durbin_watson(model_h2.resid)
print(f"Durbin-Watson Statistic: {dw_stat}")

# 6. Zero Conditional Mean of Errors: Residuals by Group
fig, ax = plt.subplots()
data_sub['Residuals'] = model_h2.resid
data_sub.boxplot(column='Residuals', by='Education', ax=ax)
plt.axhline(0, color='red', linestyle='--', linewidth=1)
plt.title("Residuals by Education Level")
plt.xlabel("Education")
plt.ylabel("Residuals")
plt.show()
```

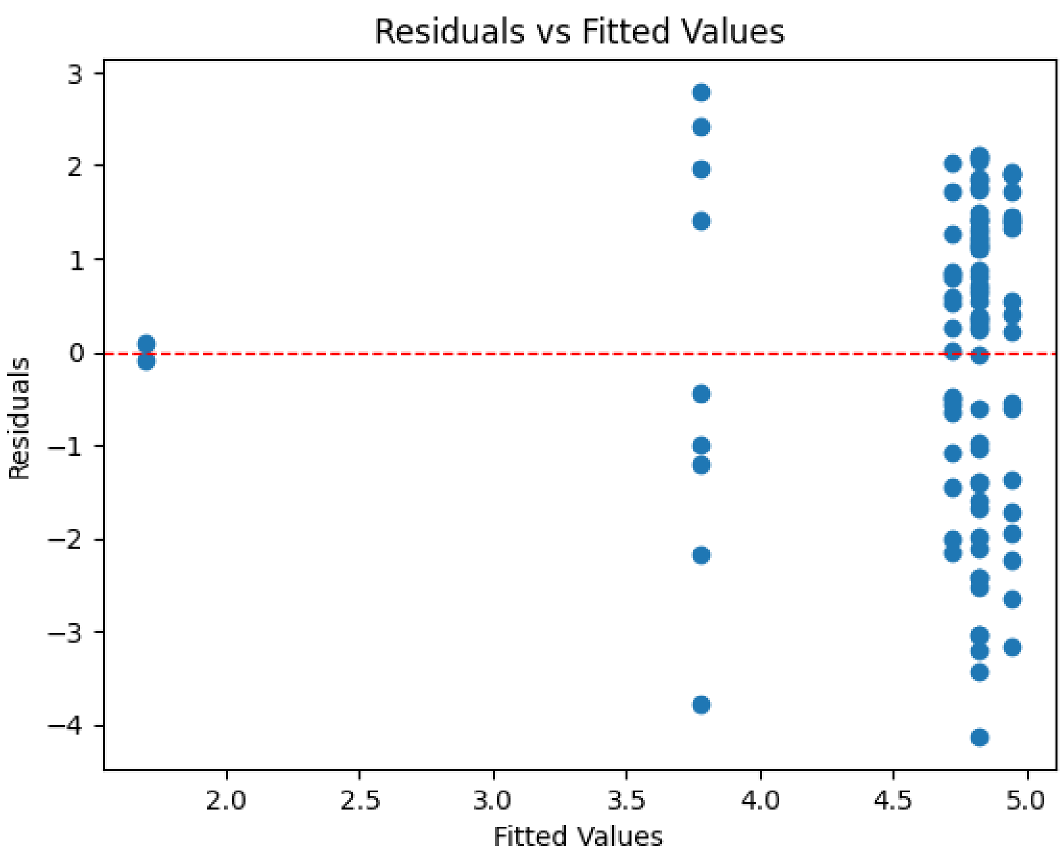
```
                            OLS Regression Results
==============================================================================
Dep. Variable:               LogWines   R-squared:                       0.093
Model:                            OLS   Adj. R-squared:                  0.054
Method:                 Least Squares   F-statistic:                     2.374
Date:                Wed, 11 Dec 2024   Prob (F-statistic):             0.0578
Time:                        16:47:21   Log-Likelihood:                -188.54
No. Observations:                  98   AIC:                             387.1
Df Residuals:                      93   BIC:                             400.0
Df Model:                           4
Covariance Type:            nonrobust
================================================================================
==============
                                coef    std err          t      P>|t|
[0.025      0.975]
--------------------------------------------------------------------------------
--------------
Intercept                     3.7750      0.567      6.659      0.000
2.649       4.901
C(Education)[T.Basic]        -2.0744      1.330     -1.560      0.122
-4.715       0.566
C(Education)[T.Graduation]    1.0467      0.616      1.700      0.093
-0.176       2.270
C(Education)[T.Master]        0.9418      0.694      1.356      0.178
-0.437       2.321
C(Education)[T.PhD]           1.1696      0.688      1.699      0.093
-0.197       2.536
==============================================================================
Omnibus:                        8.705   Durbin-Watson:                   1.932
Prob(Omnibus):                  0.013   Jarque-Bera (JB):                7.270
Skew:                          -0.572   Prob(JB):                       0.0264
Kurtosis:                       2.314   Cond. No.                         10.2
```

```
==============================================================================

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

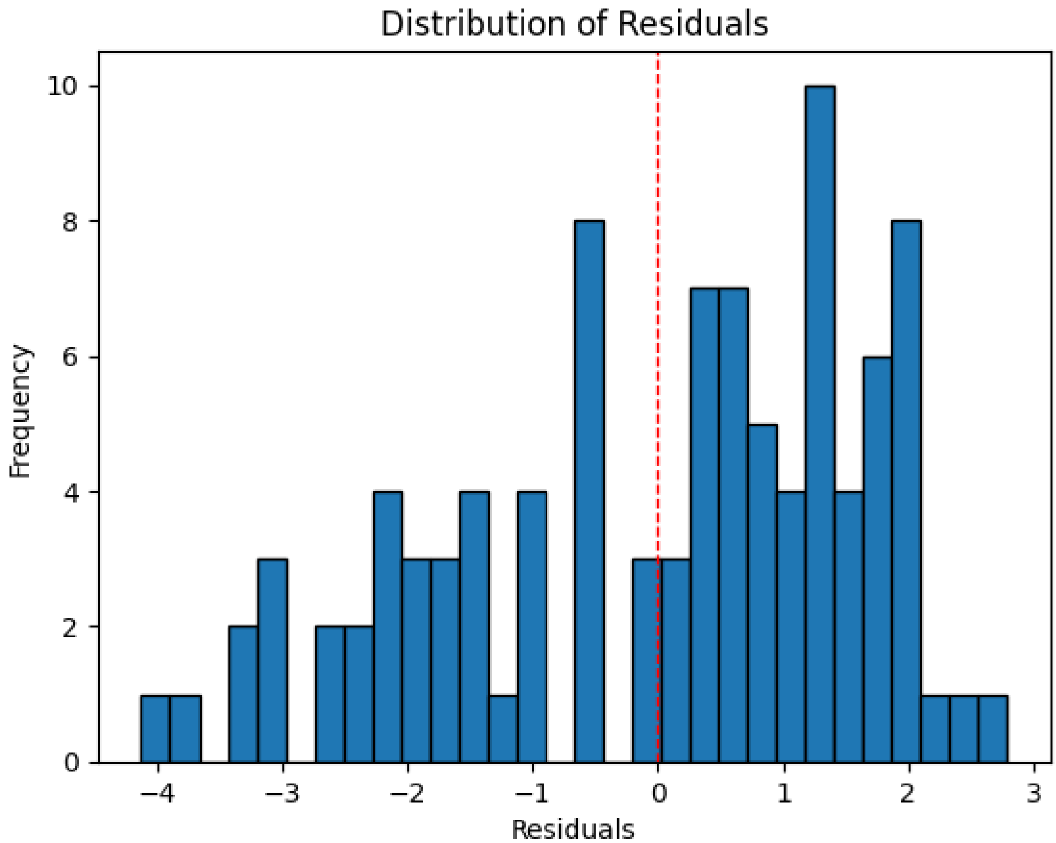



```
                            OLS Regression Results
==============================================================================
Dep. Variable:               LogWines   R-squared:                       0.093
Model:                            OLS   Adj. R-squared:                  0.054
Method:                 Least Squares   F-statistic:                     2.374
Date:                Wed, 11 Dec 2024   Prob (F-statistic):             0.0578
Time:                        16:47:22   Log-Likelihood:                -188.54
No. Observations:                  98   AIC:                             387.1
Df Residuals:                      93   BIC:                             400.0
Df Model:                           4
Covariance Type:            nonrobust
================================================================================
==============
                                 coef    std err          t      P>|t|
[0.025      0.975]
```

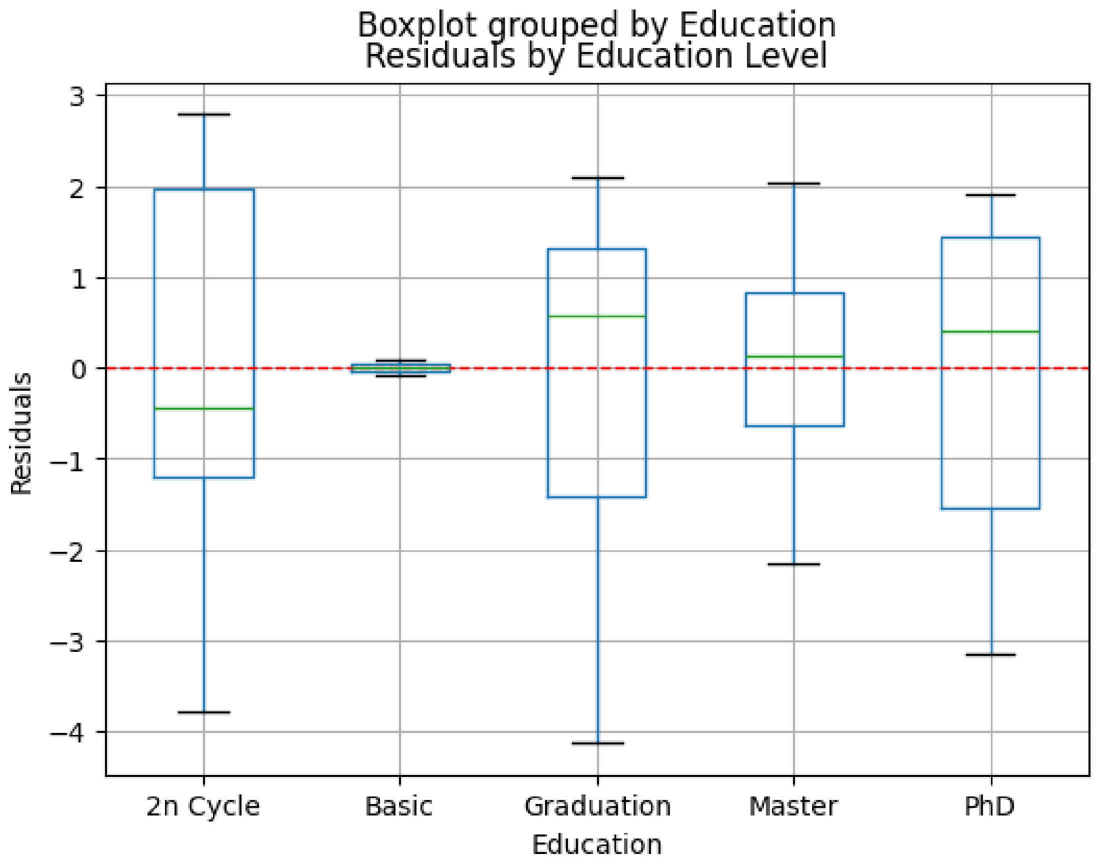
```
--------------------------------------------------------------------------------
--------------
Intercept                      3.7750      0.567      6.659      0.000
2.649       4.901
C(Education)[T.Basic]         -2.0744      1.330     -1.560      0.122
-4.715       0.566
C(Education)[T.Graduation]     1.0467      0.616      1.700      0.093
-0.176       2.270
C(Education)[T.Master]         0.9418      0.694      1.356      0.178
-0.437       2.321
C(Education)[T.PhD]            1.1696      0.688      1.699      0.093
-0.197       2.536
==============================================================================
Omnibus:                        8.705   Durbin-Watson:                   1.932
Prob(Omnibus):                  0.013   Jarque-Bera (JB):                7.270
Skew:                          -0.572   Prob(JB):                       0.0264
Kurtosis:                       2.314   Cond. No.                         10.2
==============================================================================

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



```
[[1. 0. 0. 0. 1.]
 [1. 0. 1. 0. 0.]
 [1. 0. 0. 0. 1.]
 [1. 0. 1. 0. 0.]
 [1. 1. 0. 0. 0.]]
Breusch-Pagan Test p-value: 0.08042693637853336
Shapiro-Wilk Test p-value: 0.00031816835351909455
```




```
Durbin-Watson Statistic: 1.932448290596193
```



1.5 H3

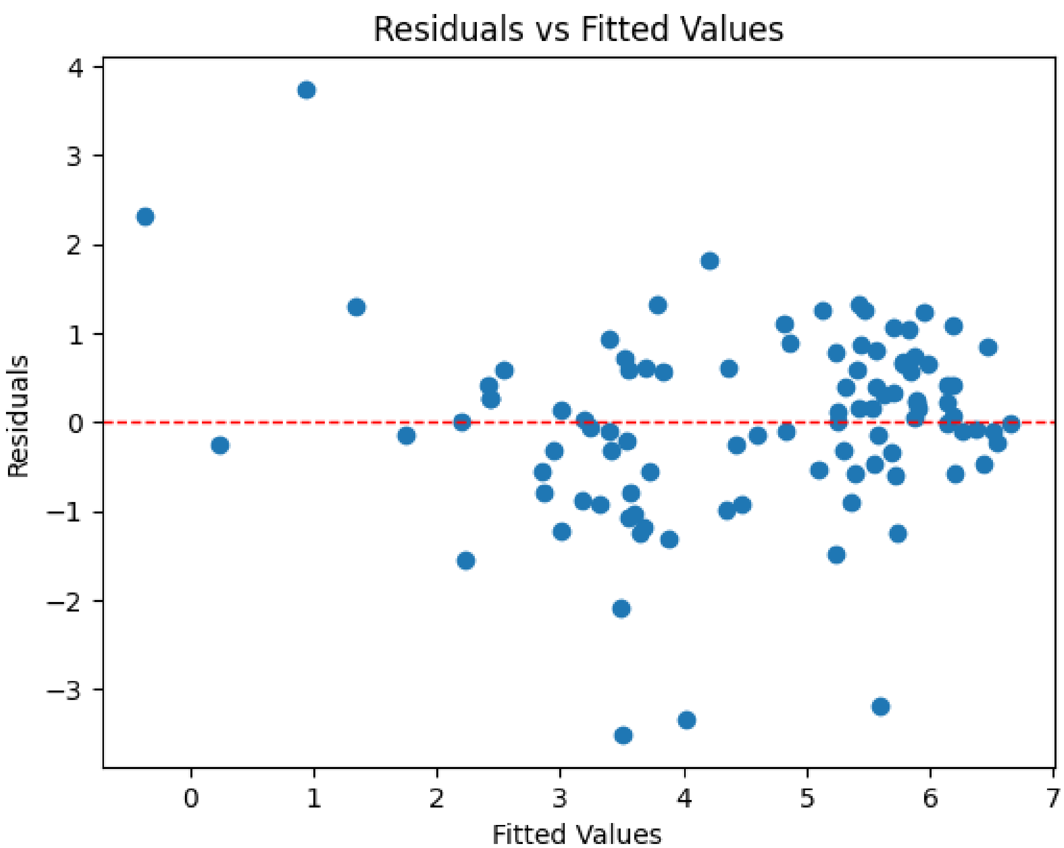
[19]:
```
# Charger le dataset
file_path = 'marketing_campaign.xlsx'
data = pd.read_excel(file_path)

# Sample and clean the data
data_sub = data.sample(100)  # Random sample of 100 rows for efficiency
data_sub['Education_numeric'] = data_sub['Education'].astype('category').cat.
 ↪codes

# Filter data to exclude high-income outliers (> 100,000) and non-positive␣
 ↪incomes
data_sub = data_sub[(data_sub['Income'] <= 100000) & (data_sub['Income'] > 0)]
data_sub['LogIncome'] = np.log(data_sub['Income'])
data_sub['LogWines'] = np.log(data_sub['MntWines'] + 1)  # Add 1 to avoid log(0)

# Hypothesis: Moderation Effect
# Interaction term for moderation effect of Kidhome
```

```python
model_h3 = ols("LogWines ~ LogIncome * C(Kidhome)", data=data_sub).fit()

# Adjust pandas display settings
pd.set_option('display.max_columns', None)
pd.set_option('display.width', 1000)

# Display summary results
print(model_h3.summary())

# ----------- OLS Assumption Checks ----------- #

# 1. Linearity: Residuals vs Fitted Plot
plt.scatter(model_h3.fittedvalues, model_h3.resid)
plt.axhline(0, color='red', linestyle='--', linewidth=1)
plt.title("Residuals vs Fitted Values")
plt.xlabel("Fitted Values")
plt.ylabel("Residuals")
plt.show()

# 2. No Perfect Multicollinearity: Variance Inflation Factor (VIF)
from statsmodels.stats.outliers_influence import variance_inflation_factor
vif = pd.DataFrame()
x_vars = model_h3.model.exog
vif["Variable"] = ["Intercept", "LogIncome", "Kidhome_1", "Kidhome_2",␣
↪"Interaction_1", "Interaction_2"]
vif["VIF"] = [variance_inflation_factor(x_vars, i) for i in range(x_vars.
↪shape[1])]
print(vif)

# 3. Homoskedasticity: Breusch-Pagan Test
from statsmodels.stats.diagnostic import het_breuschpagan
bp_test = het_breuschpagan(model_h3.resid, model_h3.model.exog)
print(f"Breusch-Pagan Test p-value: {bp_test[1]}")  # Second value is the␣
↪p-value

# 4. Normality of Residuals: Shapiro-Wilk Test
from scipy.stats import shapiro
shapiro_test = shapiro(model_h3.resid)
print(f"Shapiro-Wilk Test p-value: {shapiro_test.pvalue}")

# Plot the distribution of residuals
plt.hist(model_h3.resid, bins=30, edgecolor='black')
plt.title("Distribution of Residuals")
plt.xlabel("Residuals")
plt.ylabel("Frequency")
plt.axvline(0, color='red', linestyle='--', linewidth=1)
plt.show()
```

```python
# 5. Independence of Errors: Durbin-Watson Test
from statsmodels.stats.stattools import durbin_watson
dw_stat = durbin_watson(model_h3.resid)
print(f"Durbin-Watson Statistic: {dw_stat}")

# 6. Zero Conditional Mean of Errors: Residuals by Predictor
plt.scatter(data_sub["LogIncome"], model_h3.resid)
plt.axhline(0, color='red', linestyle='--', linewidth=1)
plt.title("Residuals vs LogIncome")
plt.xlabel("LogIncome")
plt.ylabel("Residuals")
plt.show()

# Residuals by group (Kidhome)
fig, ax = plt.subplots()
data_sub['Residuals'] = model_h3.resid
data_sub.boxplot(column='Residuals', by='Kidhome', ax=ax)
plt.axhline(0, color='red', linestyle='--', linewidth=1)
plt.title("Residuals by Kidhome Level")
plt.xlabel("Kidhome")
plt.ylabel("Residuals")
plt.show()
```

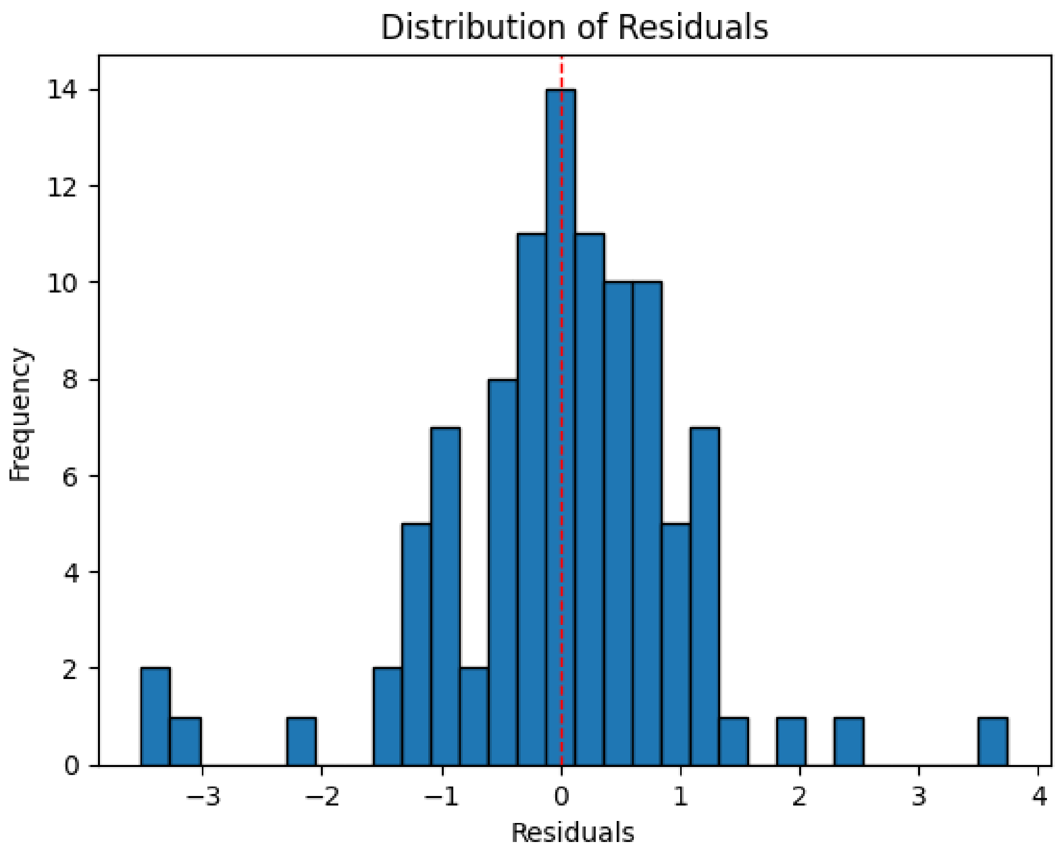
```
                            OLS Regression Results
==============================================================================
Dep. Variable:               LogWines   R-squared:                       0.674
Model:                            OLS   Adj. R-squared:                  0.657
Method:                 Least Squares   F-statistic:                     38.95
Date:                Wed, 11 Dec 2024   Prob (F-statistic):           1.75e-21
Time:                        16:50:34   Log-Likelihood:                -146.16
No. Observations:                 100   AIC:                             304.3
Df Residuals:                      94   BIC:                             320.0
Df Model:                           5
Covariance Type:            nonrobust
================================================================================
=============
                               coef    std err          t      P>|t|
[0.025      0.975]
--------------------------------------------------------------------------------
-------------
Intercept                  -18.1930      3.467     -5.247      0.000
-25.077     -11.309
C(Kidhome)[T.1]             -4.6356      5.123     -0.905      0.368
-14.808       5.537
C(Kidhome)[T.2]            -89.9748     55.962     -1.608      0.111
-201.088      21.138
```

```
LogIncome                          2.1669       0.318       6.821       0.000
1.536        2.798
LogIncome:C(Kidhome)[T.1]          0.3509       0.483       0.727       0.469
-0.608        1.309
LogIncome:C(Kidhome)[T.2]          8.3918       5.280       1.589       0.115
-2.091       18.875
==============================================================================
Omnibus:                       15.079   Durbin-Watson:                   1.928
Prob(Omnibus):                  0.001   Jarque-Bera (JB):               36.721
Skew:                          -0.456   Prob(JB):                     1.06e-08
Kurtosis:                       5.825   Cond. No.                     6.07e+03
==============================================================================

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly
specified.
[2] The condition number is large, 6.07e+03. This might indicate that there are
strong multicollinearity or other numerical problems.
```

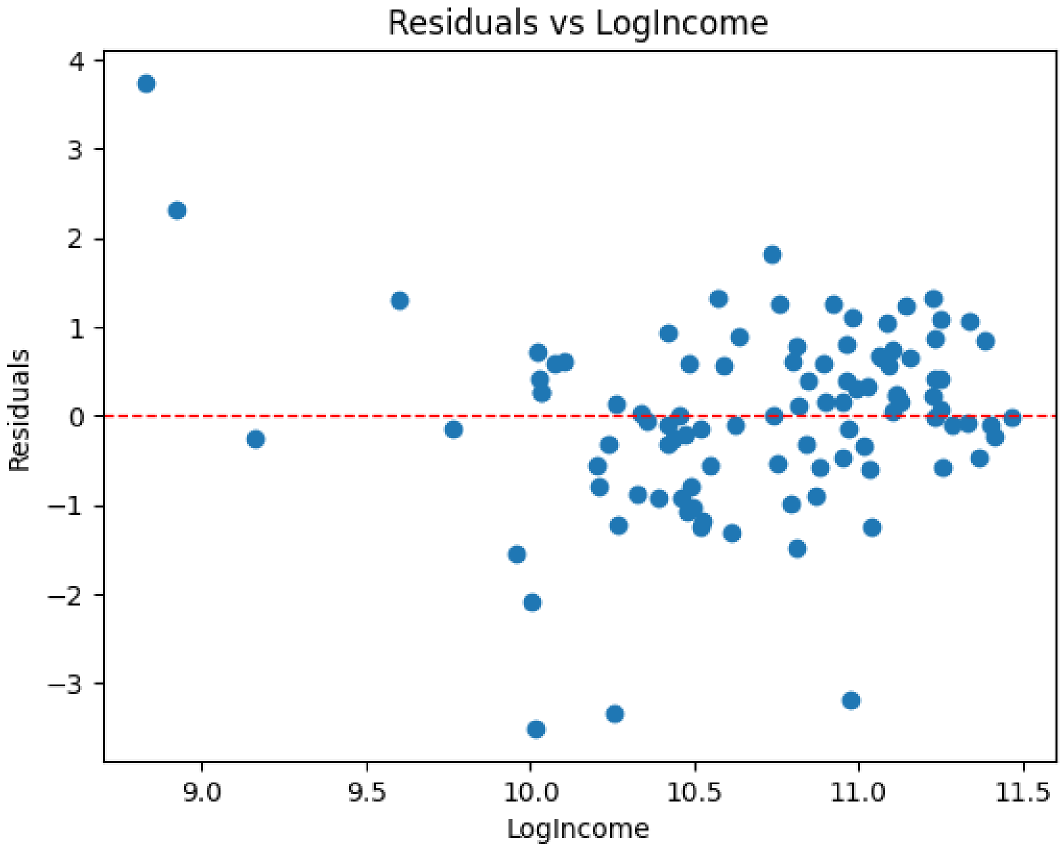


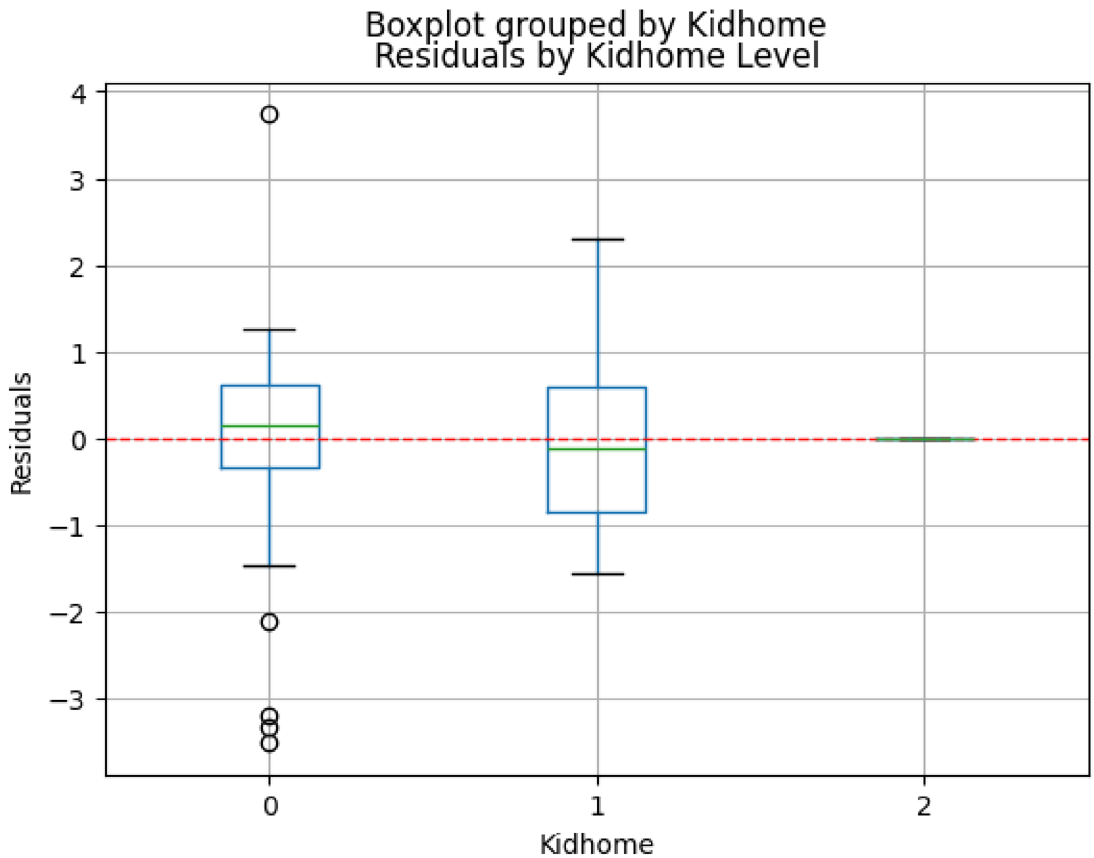

```
        Variable          VIF
```

```
0        Intercept  1037.443583
1        LogIncome   538.916222
2        Kidhome_1  5297.561628
3        Kidhome_2     2.362351
4    Interaction_1   515.925549
5    Interaction_2  5296.421147
Breusch-Pagan Test p-value: 2.2854257691510815e-07
Shapiro-Wilk Test p-value: 0.00021334826697041767
```




```
Durbin-Watson Statistic: 1.9278783705168596
```


Residuals vs LogIncome
4
3
2
1
0
−1
−2
−3
Residuals
9.0
9.5
10.0
10.5
11.0
11.5
LogIncome



1.6 BONUS

[ ]:
```python
# Hypothesis 2: Categorical Variable
model_h2 = smf.ols("MntWines ~ C(Kidhome)", data=data_sub).fit()

print(model_h2.summary())
```

```
                            OLS Regression Results
==============================================================================
Dep. Variable:               MntWines   R-squared:                       0.272
Model:                            OLS   Adj. R-squared:                  0.257
Method:                 Least Squares   F-statistic:                     17.59
Date:                Wed, 11 Dec 2024   Prob (F-statistic):           3.23e-07
Time:                        16:41:26   Log-Likelihood:                -683.54
No. Observations:                  97   AIC:                             1373.
Df Residuals:                      94   BIC:                             1381.
Df Model:                           2
Covariance Type:            nonrobust
================================================================================
===
```

```
                     coef    std err          t      P>|t|      [0.025
0.975]
--------------------------------------------------------------------------------
---
Intercept         430.4340     38.801     11.093      0.000     353.393
507.475
C(Kidhome)[T.1]  -335.2145     58.751     -5.706      0.000    -451.866
-218.563
C(Kidhome)[T.2]  -415.1006    167.640     -2.476      0.015    -747.954
-82.247
==============================================================================
Omnibus:                       32.400   Durbin-Watson:                   1.946
Prob(Omnibus):                  0.000   Jarque-Bera (JB):               67.246
Skew:                           1.281   Prob(JB):                     2.50e-15
Kurtosis:                       6.173   Cond. No.                         6.49
==============================================================================

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