```
import pandas as pd
import os
import numpy as np
import plotly as py
import warnings
warnings.filterwarnings('ignore')
import seaborn as sns
import matplotlib.pyplot as plt
from plotly.offline import init_notebook_mode
import statsmodels.api as sm
from statsmodels.formula.api import ols
import statistics
import scipy.stats as stats
from scipy.stats import kendalltau
from scipy.stats import spearmanr
from scipy.stats import pearsonr
from statsmodels.graphics.regressionplots import plot_partregress_grid
os.chdir("E:\Ginu_StudyMaterials\Sem2\Dissertation\Data")

data = pd.read_csv("PRP_FOR_DUB.csv", na_values =("N/A", "NA", "--", "
"), encoding = 'unicode_escape')
data
```

```
       date_of_sale                                      address  \
0        2010-01-01          5 Braemor Drive, Churchtown, Co.Dublin
1        2010-01-03  134 Ashewood Walk, Summerhill Lane, Portlaoise
2        2010-01-04             1 Meadow Avenue, Dundrum, Dublin 14
3        2010-01-04                         1 The Haven, Mornington
4        2010-01-04                   11 Melville Heights, Kilkenny
...             ...                                             ...
515787   2022-01-28                 Lacken, Multyfarnham, Mullingar
515788   2022-01-28                     Larch Hill, Colman, Fethard
515789   2022-01-28             Sherrys Wood, Bellewstown, Co Meath
515790   2022-01-28                  St Judes, Stoneyford, Kilkenny
515791   2022-01-28                       Sylvan, Dublin Road, Bray

       postal_code     county   price FMP VAT_exclusive
property_description  \
0              NaN     Dublin  343000  No            No
Second-Hand
1              NaN      Laois  185000  No           Yes
NewHouse
2              NaN     Dublin  438500  No            No
Second-Hand
3              NaN      Meath  400000  No            No
Second-Hand
4              NaN   Kilkenny  160000  No            No
Second-Hand
...            ...        ...     ...  ..           ...
...
```

```
515787         NaN  Westmeath  305000  No           No
Second-Hand
515788         NaN  Tipperary  300000  No           No
Second-Hand
515789         NaN      Meath  450000  No           No
Second-Hand
515790         NaN   Kilkenny  242000  No           No
Second-Hand
515791         NaN    Wicklow  620000  No           No
Second-Hand

                                property_size_description  province  \
0                                                     NaN  Leinster
1       greater than or equal to 38 sq metres and less...  Leinster
2                                                     NaN  Leinster
3                                                     NaN  Leinster
4                                                     NaN  Leinster
...                                                   ...       ...
515787                                                NaN  Leinster
515788                                                NaN   Munster
515789                                                NaN  Leinster
515790                                                NaN  Leinster
515791                                                NaN  Leinster

              lat       lon location  year  month
0       53.349764 -6.260273   Dublin  2010      1
1       52.998458 -7.398034  Outside  2010      1
2       53.349764 -6.260273   Dublin  2010      1
3       53.649784 -6.588529  Outside  2010      1
4       52.651022 -7.248495  Outside  2010      1
...           ...       ...      ...   ...    ...
515787  53.557790 -7.347856  Outside  2022      1
515788  52.684821 -7.898128  Outside  2022      1
515789  53.649784 -6.588529  Outside  2022      1
515790  52.651022 -7.248495  Outside  2022      1
515791  52.958147 -6.381971  Outside  2022      1

[515792 rows x 15 columns]
```

```
values=["Dublin"]
dub_data = data[data["location"].isin(values)]
dub_data
```

```
       date_of_sale                                     address  \
0        2010-01-01        5 Braemor Drive, Churchtown, Co.Dublin
2        2010-01-04           1 Meadow Avenue, Dundrum, Dublin 14
5        2010-01-04                  12 Sallymount Avenue, Ranelagh
11       2010-01-04      206 Philipsburgh Avenue, Marino, Dublin 3
12       2010-01-04        22 Laverna Way, Castleknock, Dublin 15
...             ...                                           ...
```

```
515765   2022-01-28      22 Stanford, Ardilea, Clonskeagh Dublin 14
515767   2022-01-28  26 Melville Court, Cityside, Finglas Dublin 11
515772   2022-01-28        52 Park Dr Grove, Castleknock, Dublin 15
515777   2022-01-28    Apartment 7, Parkgate Place, Parkgate Street
515778   2022-01-28             Apt 15, The Atrium, 29 31 Island St

       postal_code  county   price FMP VAT_exclusive
property_description  \
0              NaN  Dublin  343000  No            No          Second-
Hand
2              NaN  Dublin  438500  No            No          Second-
Hand
5              NaN  Dublin  425000  No            No          Second-
Hand
11             NaN  Dublin  430000  No            No          Second-
Hand
12             NaN  Dublin  355000  No            No          Second-
Hand
...            ...     ...     ...  ..           ...
...
515765   Dublin 14  Dublin  425000  No            No          Second-
Hand
515767   Dublin 11  Dublin  270000  No            No          Second-
Hand
515772   Dublin 15  Dublin  386000  No            No          Second-
Hand
515777         NaN  Dublin  367500  No            No          Second-
Hand
515778    Dublin 8  Dublin  260000  No            No          Second-
Hand

       property_size_description  province        lat       lon
location  \
0                            NaN  Leinster  53.349764 -6.260273
Dublin
2                            NaN  Leinster  53.349764 -6.260273
Dublin
5                            NaN  Leinster  53.349764 -6.260273
Dublin
11                           NaN  Leinster  53.349764 -6.260273
Dublin
12                           NaN  Leinster  53.349764 -6.260273
Dublin
...                          ...       ...        ...       ...       .
..
515765                       NaN  Leinster  53.349764 -6.260273
Dublin
515767                       NaN  Leinster  53.349764 -6.260273
Dublin
515772                       NaN  Leinster  53.349764 -6.260273
```

```
Dublin
515777                         NaN  Leinster  53.349764 -6.260273
Dublin
515778                         NaN  Leinster  53.349764 -6.260273
Dublin

        year  month
0       2010      1
2       2010      1
5       2010      1
11      2010      1
12      2010      1
...      ...    ...
515765  2022      1
515767  2022      1
515772  2022      1
515777  2022      1
515778  2022      1

[164027 rows x 15 columns]
```

```
dub_data.to_csv("PRP_Dublin.csv", index=False)
```

Statistical Analyses

```
#### MLR

for col in dub_data.columns:
    print(col)
```

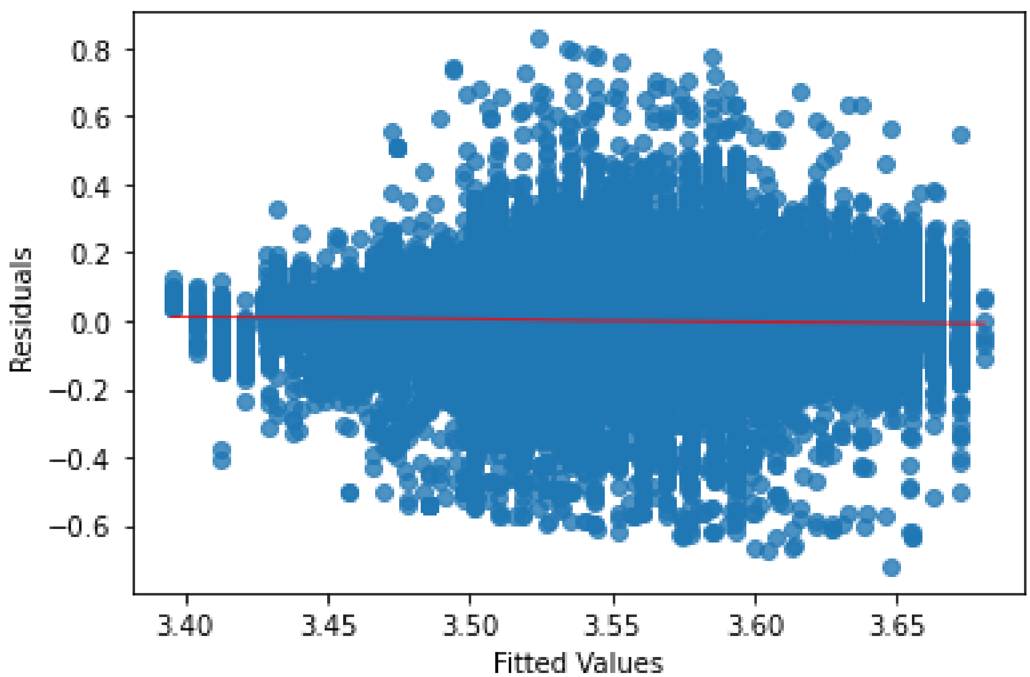
```
date_of_sale
address
postal_code
county
price
FMP
VAT_exclusive
property_description
property_size_description
province
lat
lon
location
year
month
```

```
counties = dub_data['county'].unique()
counties
```

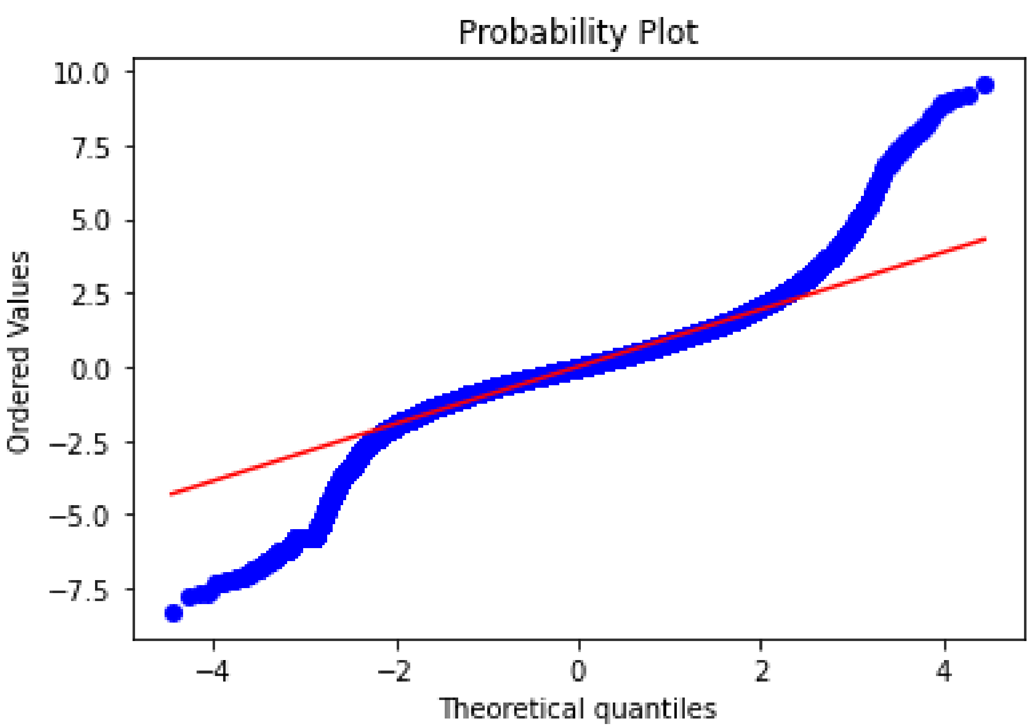
```
array(['Dublin'], dtype=object)
```

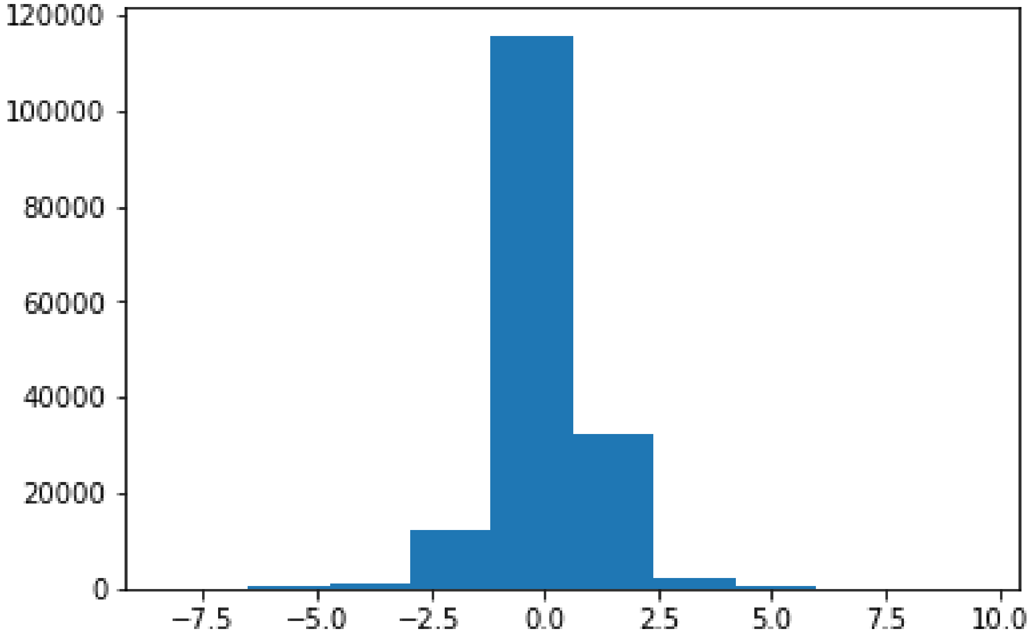
```
rppr1 = dub_data.copy()
rppr1.drop(columns
=['date_of_sale','address','VAT_exclusive','FMP','county','location','
province'], inplace=True)

#rppr1["location_Dublin"]=pd.get_dummies(rppr1["location"])["Dublin"]

rppr1["property_new"]=pd.get_dummies(rppr1["property_description"])
["NewHouse"]

rppr1["postal_code_Dublin 14"]=pd.get_dummies(rppr1["postal_code"])
["Dublin 14"]
rppr1["postal_code_Dublin 2"]=pd.get_dummies(rppr1["postal_code"])
["Dublin 2"]
rppr1["postal_code_Dublin 13"]=pd.get_dummies(rppr1["postal_code"])
["Dublin 13"]
rppr1["postal_code_Dublin 12"]=pd.get_dummies(rppr1["postal_code"])
["Dublin 12"]
rppr1["postal_code_Dublin 4"]=pd.get_dummies(rppr1["postal_code"])
["Dublin 4"]
rppr1["postal_code_Dublin 11"]=pd.get_dummies(rppr1["postal_code"])
["Dublin 11"]
rppr1["postal_code_Dublin 9"]=pd.get_dummies(rppr1["postal_code"])
["Dublin 9"]
rppr1["postal_code_Dublin 10"]=pd.get_dummies(rppr1["postal_code"])
["Dublin 10"]
rppr1["postal_code_Dublin 15"]=pd.get_dummies(rppr1["postal_code"])
["Dublin 15"]
rppr1["postal_code_Dublin 22"]=pd.get_dummies(rppr1["postal_code"])
["Dublin 22"]
rppr1["postal_code_Dublin 5"]=pd.get_dummies(rppr1["postal_code"])
["Dublin 5"]
rppr1["postal_code_Dublin 18"]=pd.get_dummies(rppr1["postal_code"])
["Dublin 18"]
rppr1["postal_code_Dublin 6"]=pd.get_dummies(rppr1["postal_code"])
["Dublin 6"]
rppr1["postal_code_Dublin 6w"]=pd.get_dummies(rppr1["postal_code"])
["Dublin 6w"]
rppr1["postal_code_Dublin 17"]=pd.get_dummies(rppr1["postal_code"])
["Dublin 17"]
rppr1["postal_code_Dublin 16"]=pd.get_dummies(rppr1["postal_code"])
["Dublin 16"]
rppr1["postal_code_Dublin 8"]=pd.get_dummies(rppr1["postal_code"])
["Dublin 8"]
rppr1["postal_code_Dublin 3"]=pd.get_dummies(rppr1["postal_code"])
["Dublin 3"]
rppr1["postal_code_Dublin 1"]=pd.get_dummies(rppr1["postal_code"])
["Dublin 1"]
rppr1["postal_code_Dublin 17"]=pd.get_dummies(rppr1["postal_code"])
["Dublin 17"]
```

```
rppr1["postal_code_Dublin 20"]=pd.get_dummies(rppr1["postal_code"])
["Dublin 20"]

from numpy import sqrt
log_price = np.log(rppr1['price'])
transform  = sqrt(log_price)

X = rppr1[["property_new","year","lat","lon","postal_code_Dublin
14","postal_code_Dublin 2","postal_code_Dublin 13","postal_code_Dublin
12","postal_code_Dublin 4","postal_code_Dublin 11","postal_code_Dublin
9","postal_code_Dublin 10","postal_code_Dublin 15","postal_code_Dublin
22","postal_code_Dublin 5","postal_code_Dublin 18","postal_code_Dublin
6","postal_code_Dublin 6w","postal_code_Dublin 17","postal_code_Dublin
16","postal_code_Dublin 8","postal_code_Dublin 3","postal_code_Dublin
1","postal_code_Dublin 17","postal_code_Dublin 20"]]
X = sm.add_constant(X)
y = transform
#X.head(20)

model_full_mlr = sm.OLS(y, X).fit()

#fitted values
model_fitted_vals = model_full_mlr.fittedvalues
#model residuals
model_residuals = model_full_mlr.resid
#standardised residuals
model_norm_residuals =
model_full_mlr.get_influence().resid_studentized_internal

sns.regplot(x=model_fitted_vals,y=model_residuals,
 ci=False,lowess=True,
 line_kws={'color': 'red', 'lw': 1, 'alpha': 0.8})
plt.xlabel("Fitted Values")
plt.ylabel("Residuals")
plt.show()
```




```
stats.probplot(model_norm_residuals, plot=sns.mpl.pyplot)
plt.show()

plt.hist(model_norm_residuals)
plt.show()
```





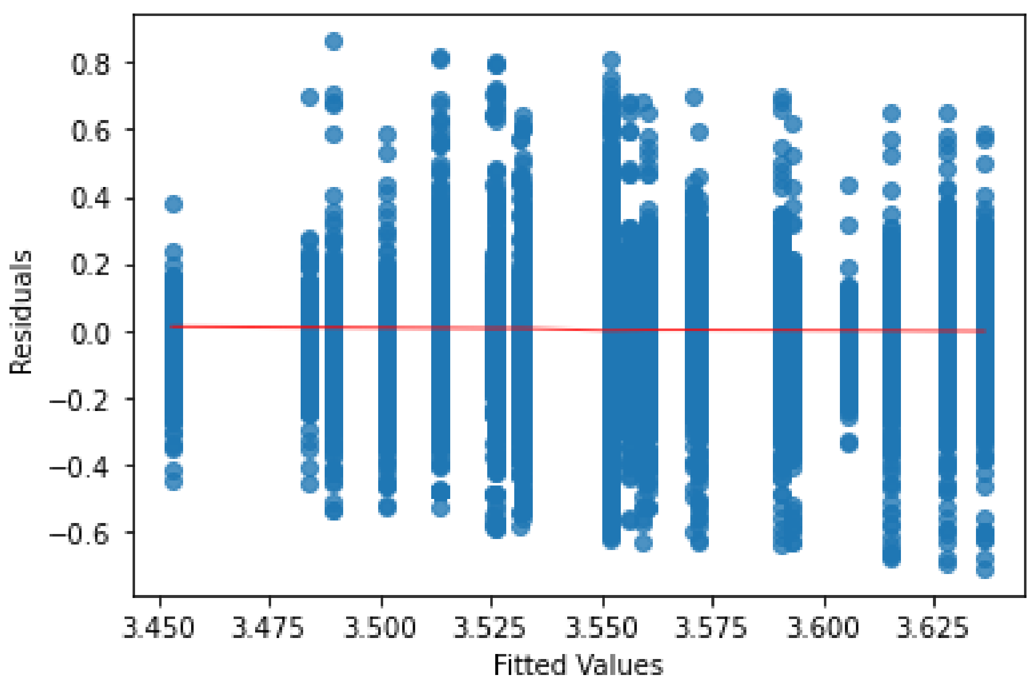

```
from statsmodels.formula.api import ols
model_full_mlr1 = ols('log_price ~ lat+lon+C(year)+C(postal_code)
+C(property_description)', data=rppr1).fit()
model_full_mlr1.summary()

<class 'statsmodels.iolib.summary.Summary'>
"""
                            OLS Regression Results

======================================================================
========
Dep. Variable:              log_price   R-squared:
0.281
Model:                            OLS   Adj. R-squared:
0.281
Method:                 Least Squares   F-statistic:
1114.
Date:                Thu, 04 Aug 2022   Prob (F-statistic):
0.00
Time:                        18:58:22   Log-Likelihood:
-85320.
No. Observations:               96825   AIC:
1.707e+05
Df Residuals:                   96790   BIC:
1.710e+05
Df Model:                          34

Covariance Type:            nonrobust

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

```
====================================
                                              coef    std err
t      P>|t|      [0.025      0.975]
----------------------------------------------------------------------------
------------------------------------
Intercept                                   0.0042   5.72e-06
738.484      0.000       0.004       0.004
C(year)[T.2011]                            -0.1707      0.018     -
9.306      0.000      -0.207      -0.135
C(year)[T.2012]                            -0.3598      0.017    -
21.785      0.000      -0.392      -0.327
C(year)[T.2013]                            -0.3115      0.014    -
21.745      0.000      -0.340      -0.283
C(year)[T.2014]                             0.0155      0.013
1.161      0.246      -0.011       0.042
C(year)[T.2015]                             0.0426      0.013
3.282      0.001       0.017       0.068
C(year)[T.2016]                             0.1505      0.013
11.594      0.000       0.125       0.176
C(year)[T.2017]                             0.2476      0.013
19.247      0.000       0.222       0.273
C(year)[T.2018]                             0.3112      0.013
24.226      0.000       0.286       0.336
C(year)[T.2019]                             0.3415      0.013
26.628      0.000       0.316       0.367
C(year)[T.2020]                             0.3530      0.013
26.979      0.000       0.327       0.379
C(year)[T.2021]                             0.4218      0.013
32.555      0.000       0.396       0.447
C(year)[T.2022]                             0.4276      0.033
12.810      0.000       0.362       0.493
C(postal_code)[T.Dublin 10]                -0.4472      0.019    -
23.316      0.000      -0.485      -0.410
C(postal_code)[T.Dublin 11]                -0.1914      0.013    -
14.493      0.000      -0.217      -0.166
C(postal_code)[T.Dublin 12]                 0.0959      0.013
7.152      0.000       0.070       0.122
C(postal_code)[T.Dublin 13]                 0.2814      0.013
21.027      0.000       0.255       0.308
C(postal_code)[T.Dublin 14]                 0.6939      0.014
51.312      0.000       0.667       0.720
C(postal_code)[T.Dublin 15]                 0.0859      0.012
7.312      0.000       0.063       0.109
C(postal_code)[T.Dublin 16]                 0.5269      0.014
38.632      0.000       0.500       0.554
C(postal_code)[T.Dublin 17]                -0.2279      0.020    -
11.206      0.000      -0.268      -0.188
C(postal_code)[T.Dublin 18]                 0.5082      0.013
40.264      0.000       0.483       0.533
C(postal_code)[T.Dublin 2]                  0.3986      0.017
```

```
23.379      0.000       0.365       0.432
C(postal_code)[T.Dublin 20]                   0.0559      0.020
2.781      0.005       0.016       0.095
C(postal_code)[T.Dublin 22]                  -0.1576      0.015    -
10.484      0.000      -0.187      -0.128
C(postal_code)[T.Dublin 24]                  -0.0353      0.013     -
2.797      0.005      -0.060      -0.011
C(postal_code)[T.Dublin 3]                    0.3954      0.014
28.810      0.000       0.368       0.422
C(postal_code)[T.Dublin 4]                    0.7969      0.013
61.177      0.000       0.771       0.822
C(postal_code)[T.Dublin 5]                    0.2962      0.014
21.047      0.000       0.269       0.324
C(postal_code)[T.Dublin 6]                    0.8627      0.014
62.887      0.000       0.836       0.890
C(postal_code)[T.Dublin 6w]                   0.7735      0.024
32.492      0.000       0.727       0.820
C(postal_code)[T.Dublin 7]                    0.1446      0.013
11.018      0.000       0.119       0.170
C(postal_code)[T.Dublin 8]                    0.0656      0.013
5.067      0.000       0.040       0.091
C(postal_code)[T.Dublin 9]                    0.2663      0.013
20.359      0.000       0.241       0.292
C(property_description)[T.Second-Hand]        0.0161      0.006
2.710      0.007       0.004       0.028
lat                                           0.2252      0.000
738.484      0.000       0.225       0.226
lon                                          -0.0264   3.58e-05   -
738.484      0.000      -0.026      -0.026
======================================================================
========
Omnibus:                    16685.870   Durbin-Watson:
1.696
Prob(Omnibus):                  0.000   Jarque-Bera (JB):
391302.189
Skew:                           0.042   Prob(JB):
0.00
Kurtosis:                      12.848   Cond. No.
4.08e+15
======================================================================
========

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is
correctly specified.
[2] The smallest eigenvalue is 1.68e-23. This might indicate that
there are
strong multicollinearity problems or that the design matrix is
singular.
"""
```

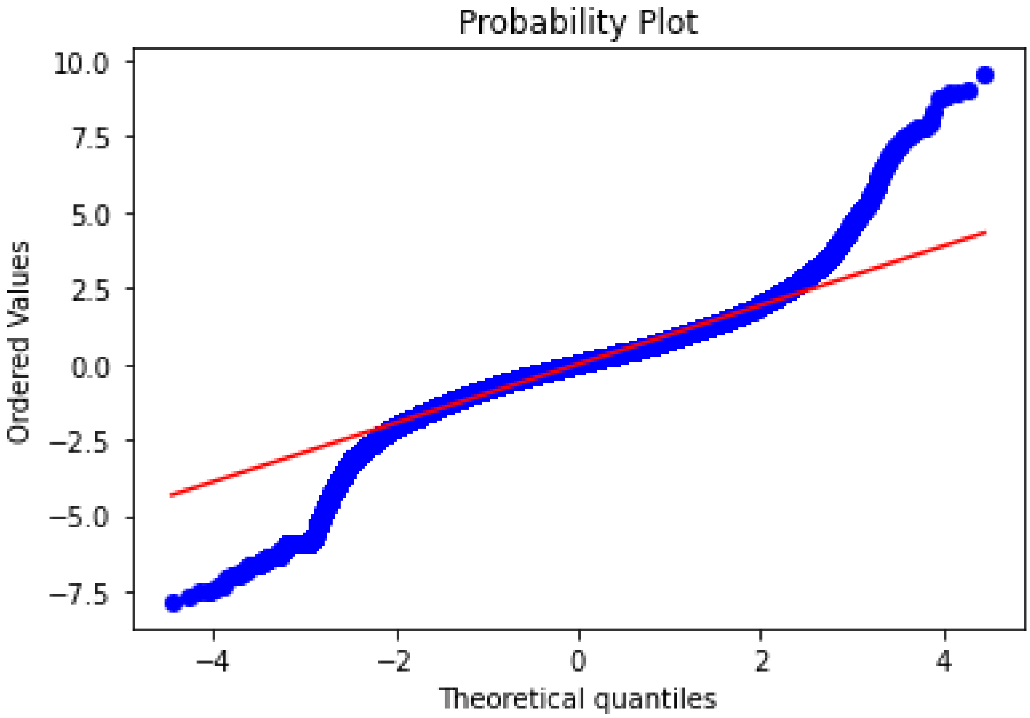
```
SLR
rppr1 = dub_data.copy()
log_price = np.log(rppr1['price'])
transform  = sqrt(log_price)

rppr1["postal_code_Dublin 14"]=pd.get_dummies(rppr1["postal_code"])
["Dublin 14"]
rppr1["postal_code_Dublin 2"]=pd.get_dummies(rppr1["postal_code"])
["Dublin 2"]
rppr1["postal_code_Dublin 13"]=pd.get_dummies(rppr1["postal_code"])
["Dublin 13"]
rppr1["postal_code_Dublin 12"]=pd.get_dummies(rppr1["postal_code"])
["Dublin 12"]
rppr1["postal_code_Dublin 4"]=pd.get_dummies(rppr1["postal_code"])
["Dublin 4"]
rppr1["postal_code_Dublin 11"]=pd.get_dummies(rppr1["postal_code"])
["Dublin 11"]
rppr1["postal_code_Dublin 9"]=pd.get_dummies(rppr1["postal_code"])
["Dublin 9"]
rppr1["postal_code_Dublin 10"]=pd.get_dummies(rppr1["postal_code"])
["Dublin 10"]
rppr1["postal_code_Dublin 15"]=pd.get_dummies(rppr1["postal_code"])
["Dublin 15"]
rppr1["postal_code_Dublin 22"]=pd.get_dummies(rppr1["postal_code"])
["Dublin 22"]
rppr1["postal_code_Dublin 5"]=pd.get_dummies(rppr1["postal_code"])
["Dublin 5"]
rppr1["postal_code_Dublin 18"]=pd.get_dummies(rppr1["postal_code"])
["Dublin 18"]
rppr1["postal_code_Dublin 6"]=pd.get_dummies(rppr1["postal_code"])
["Dublin 6"]
rppr1["postal_code_Dublin 6w"]=pd.get_dummies(rppr1["postal_code"])
["Dublin 6w"]
rppr1["postal_code_Dublin 17"]=pd.get_dummies(rppr1["postal_code"])
["Dublin 17"]
rppr1["postal_code_Dublin 16"]=pd.get_dummies(rppr1["postal_code"])
["Dublin 16"]
rppr1["postal_code_Dublin 8"]=pd.get_dummies(rppr1["postal_code"])
["Dublin 8"]
rppr1["postal_code_Dublin 3"]=pd.get_dummies(rppr1["postal_code"])
["Dublin 3"]
rppr1["postal_code_Dublin 1"]=pd.get_dummies(rppr1["postal_code"])
["Dublin 1"]
rppr1["postal_code_Dublin 17"]=pd.get_dummies(rppr1["postal_code"])
["Dublin 17"]
rppr1["postal_code_Dublin 20"]=pd.get_dummies(rppr1["postal_code"])
["Dublin 20"]

# Try SLR
import numpy as np
```

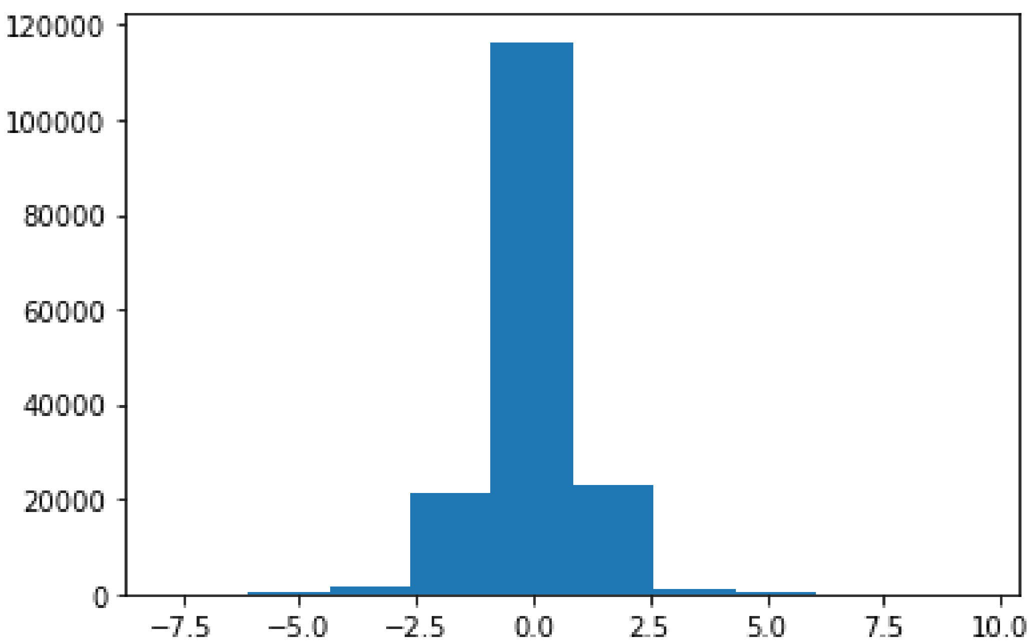
```
X = rppr1[["postal_code_Dublin 14","postal_code_Dublin
2","postal_code_Dublin 13","postal_code_Dublin 12","postal_code_Dublin
4","postal_code_Dublin 11","postal_code_Dublin 9","postal_code_Dublin
10","postal_code_Dublin 15","postal_code_Dublin
22","postal_code_Dublin 5","postal_code_Dublin 18","postal_code_Dublin
6","postal_code_Dublin 6w","postal_code_Dublin 17","postal_code_Dublin
16","postal_code_Dublin 8","postal_code_Dublin 3","postal_code_Dublin
1","postal_code_Dublin 17","postal_code_Dublin 20"]]
X = sm.add_constant(X)
y = transform
model_slr = sm.OLS(y, X).fit()


#fitted values
model_fitted_vals = model_slr.fittedvalues
#model residuals
model_residuals = model_slr.resid
#standardised residuals
model_norm_residuals =
model_slr.get_influence().resid_studentized_internal

sns.regplot(x=model_fitted_vals,y=model_residuals,
ci=False,lowess=True,
line_kws={'color': 'red', 'lw': 1, 'alpha': 0.8})
plt.xlabel("Fitted Values")
plt.ylabel("Residuals")
plt.show()
```




```
stats.probplot(model_norm_residuals, plot=sns.mpl.pyplot)
plt.show()
```

```
plt.hist(model_norm_residuals)
plt.show()
```






```
from statsmodels.formula.api import ols
model_full_mlr1 = ols('log_price ~ C(postal_code)', data=rppr1).fit()
model_full_mlr1.summary()
```

```
<class 'statsmodels.iolib.summary.Summary'>
"""
                            OLS Regression Results

======================================================================
========
Dep. Variable:              log_price   R-squared:
0.192
Model:                            OLS   Adj. R-squared:
0.192
Method:                 Least Squares   F-statistic:
1099.
Date:                Fri, 05 Aug 2022   Prob (F-statistic):
0.00
Time:                        11:01:20   Log-Likelihood:
-90954.
No. Observations:               96825   AIC:
1.820e+05
Df Residuals:                   96803   BIC:
1.822e+05
Df Model:                          21

Covariance Type:            nonrobust

======================================================================
=========================
                                  coef    std err          t      P>|
t|      [0.025      0.975]
----------------------------------------------------------------------
-------------------------
Intercept                      12.3552      0.011   1119.318
0.000      12.334      12.377
C(postal_code)[T.Dublin 10]    -0.4243      0.020    -20.879
0.000      -0.464      -0.384
C(postal_code)[T.Dublin 11]    -0.1709      0.014    -12.223
0.000      -0.198      -0.143
C(postal_code)[T.Dublin 12]     0.1221      0.014      8.604
0.000       0.094       0.150
C(postal_code)[T.Dublin 13]     0.3297      0.014     23.336
0.000       0.302       0.357
C(postal_code)[T.Dublin 14]     0.7217      0.014     50.397
0.000       0.694       0.750
C(postal_code)[T.Dublin 15]     0.1306      0.012     10.538
0.000       0.106       0.155
C(postal_code)[T.Dublin 16]     0.5594      0.014     38.753
0.000       0.531       0.588
C(postal_code)[T.Dublin 17]    -0.2118      0.022     -9.843
0.000      -0.254      -0.170
C(postal_code)[T.Dublin 18]     0.5427      0.013     40.758
0.000       0.517       0.569
```

```
C(postal_code)[T.Dublin 2]       0.4033      0.018     22.324
0.000       0.368       0.439
C(postal_code)[T.Dublin 20]      0.0825      0.021      3.880
0.000       0.041       0.124
C(postal_code)[T.Dublin 22]     -0.0914      0.016     -5.742
0.000      -0.123      -0.060
C(postal_code)[T.Dublin 24]      0.0399      0.013      2.995
0.003       0.014       0.066
C(postal_code)[T.Dublin 3]       0.4124      0.015     28.371
0.000       0.384       0.441
C(postal_code)[T.Dublin 4]       0.8159      0.014     59.150
0.000       0.789       0.843
C(postal_code)[T.Dublin 5]       0.3172      0.015     21.288
0.000       0.288       0.346
C(postal_code)[T.Dublin 6]       0.8800      0.015     60.569
0.000       0.852       0.908
C(postal_code)[T.Dublin 6w]      0.6512      0.025     26.119
0.000       0.602       0.700
C(postal_code)[T.Dublin 7]       0.1673      0.014     12.044
0.000       0.140       0.195
C(postal_code)[T.Dublin 8]       0.0895      0.014      6.522
0.000       0.063       0.116
C(postal_code)[T.Dublin 9]       0.2975      0.014     21.498
0.000       0.270       0.325
======================================================================
========
Omnibus:                    16165.422   Durbin-Watson:
1.511
Prob(Omnibus):                  0.000   Jarque-Bera (JB):
311906.290
Skew:                          -0.192   Prob(JB):
0.00
Kurtosis:                      11.784   Cond. No.
27.5
======================================================================
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Notes:
[1] Standard Errors assume that the covariance matrix of the errors is
correctly specified.
"""
```