

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
```

```
df = pd.read_stata('wage.dta')
```

```
df.head()
```

```
↗
```

	w	fe	nw	un	ed	ex	age	wk
0	11.55	1.0	0.0	0.0	12.0	20.0	38.0	1.0
1	5.00	0.0	0.0	0.0	9.0	9.0	24.0	0.0
2	12.00	0.0	0.0	0.0	16.0	15.0	37.0	1.0
3	7.00	0.0	1.0	1.0	14.0	38.0	58.0	0.0
4	21.15	1.0	1.0	0.0	16.0	19.0	41.0	1.0

```
df.describe()
```

```
↗
```

	w	fe	nw	un	ed	ex	age	wk
count	1289.000000	1289.000000	1289.000000	1289.000000	1289.000000	1289.000000	1289.000000	1289.000000
mean	12.365849	0.497285	0.152832	0.159038	13.145074	18.789759	37.934834	0.407292
std	7.896350	0.500187	0.359965	0.365853	2.813823	11.662837	11.494278	0.491521
min	0.840000	0.000000	0.000000	0.000000	0.000000	0.000000	18.000000	0.000000
25%	6.920000	0.000000	0.000000	0.000000	12.000000	9.000000	29.000000	0.000000
50%	10.080000	0.000000	0.000000	0.000000	12.000000	18.000000	37.000000	0.000000
75%	15.630000	1.000000	0.000000	0.000000	16.000000	27.000000	47.000000	1.000000
max	64.080002	1.000000	1.000000	1.000000	20.000000	56.000000	65.000000	1.000000

```
df.info()
```

```
↗
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1289 entries, 0 to 1288
Data columns (total 8 columns):
#   Column  Non-Null Count  Dtype
---  -
0    w      1289 non-null    float32
1    fe      1289 non-null    float32
2    nw      1289 non-null    float32
3    un      1289 non-null    float32
4    ed      1289 non-null    float32
5    ex      1289 non-null    float32
6    age     1289 non-null    float32
7    wk      1289 non-null    float32
dtypes: float32(8)
memory usage: 40.4 KB
```

```
df.to_csv('wage.csv', index= False)
```

```
df['ln(wage)'] = np.log(df['w'])
```

```
df.head()
```

```
↗
```

	w	fe	nw	un	ed	ex	age	wk	ln(wage)
0	11.55	1.0	0.0	0.0	12.0	20.0	38.0	1.0	2.446686
1	5.00	0.0	0.0	0.0	9.0	9.0	24.0	0.0	1.609438
2	12.00	0.0	0.0	0.0	16.0	15.0	37.0	1.0	2.484907
3	7.00	0.0	1.0	1.0	14.0	38.0	58.0	0.0	1.945910
4	21.15	1.0	1.0	0.0	16.0	19.0	41.0	1.0	3.051640

```
# Count the occurrences of female values
fe_counts = df['fe'].value_counts()

# Define the labels and sizes for the pie chart
labels = ['female', 'male']
sizes = [fe_counts[1.0], fe_counts[0.0]]

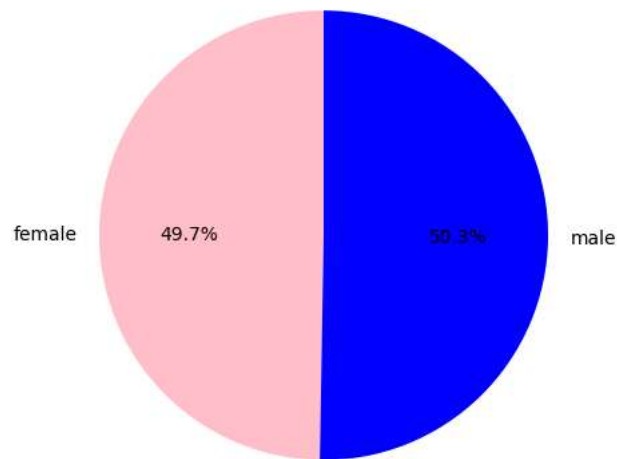
# Plot the pie chart
plt.pie(sizes, labels=labels, autopct='%1.1f%%', startangle=90, colors=['pink', 'blue'])

# Equal aspect ratio ensures that pie chart is drawn as a circle.
plt.axis('equal')

# Show the plot
plt.title('Distribution of female and male population')
plt.show()
```



Distribution of female and male population



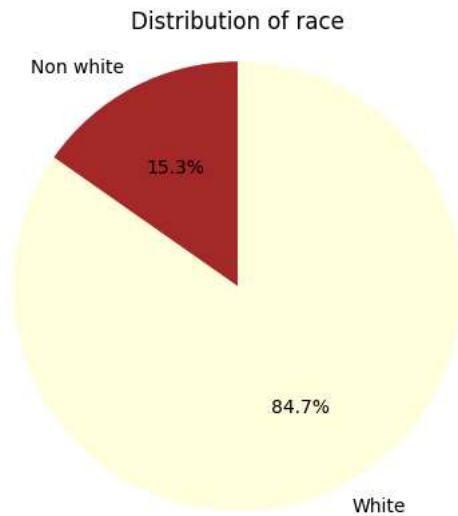
```
# Count the occurrences of fe values
nw_counts = df['nw'].value_counts()

# Define the labels and sizes for the pie chart
labels = ['Non white', 'White']
sizes = [nw_counts[1.0], nw_counts[0.0]]

# Plot the pie chart
plt.pie(sizes, labels=labels, autopct='%1.1f%%', startangle=90, colors=['brown', 'lightyellow'])

# Equal aspect ratio ensures that pie chart is drawn as a circle.
plt.axis('equal')

# Show the plot
plt.title('Distribution of race')
plt.show()
```



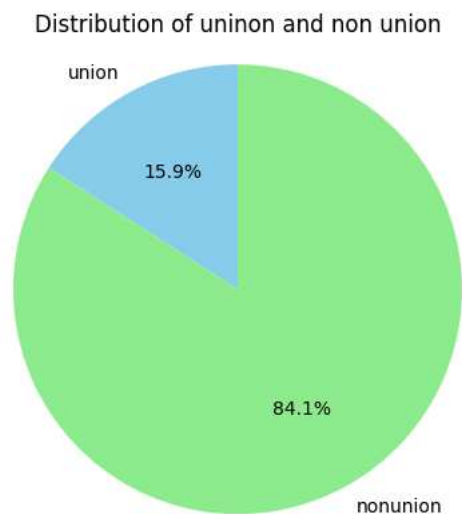
```
#Count the occurrences of un values
un_counts = df['un'].value_counts()

# Define the labels and sizes for the pie chart
labels = ['union', 'nonunion']
sizes = [un_counts[1.0], un_counts[0.0]]

# Plot the pie chart
plt.pie(sizes, labels=labels, autopct='%1.1f%%', startangle=90, colors=['skyblue', 'lightgreen'])

# Equal aspect ratio ensures that pie chart is drawn as a circle.
plt.axis('equal')

# Show the plot
plt.title('Distribution of union and non union')
plt.show()
```



```
# Count the occurrences of fe values
wk_counts = df['wk'].value_counts()

# Define the labels and sizes for the pie chart
labels = ['weekly', 'non weekly']
sizes = [wk_counts[1.0], wk_counts[0.0]]

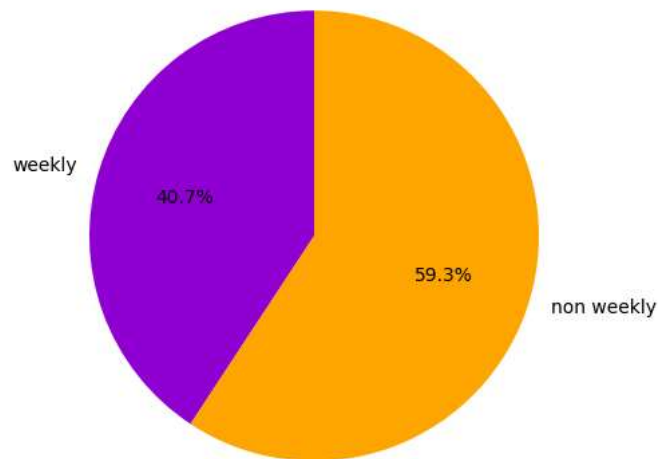
# Plot the pie chart
plt.pie(sizes, labels=labels, autopct='%1.1f%%', startangle=90, colors=['darkviolet', 'orange'])

# Equal aspect ratio ensures that pie chart is drawn as a circle.
plt.axis('equal')
```

```
# Show the plot
plt.title('Distribution of weekly and non weekly wage earner')
plt.show()
```



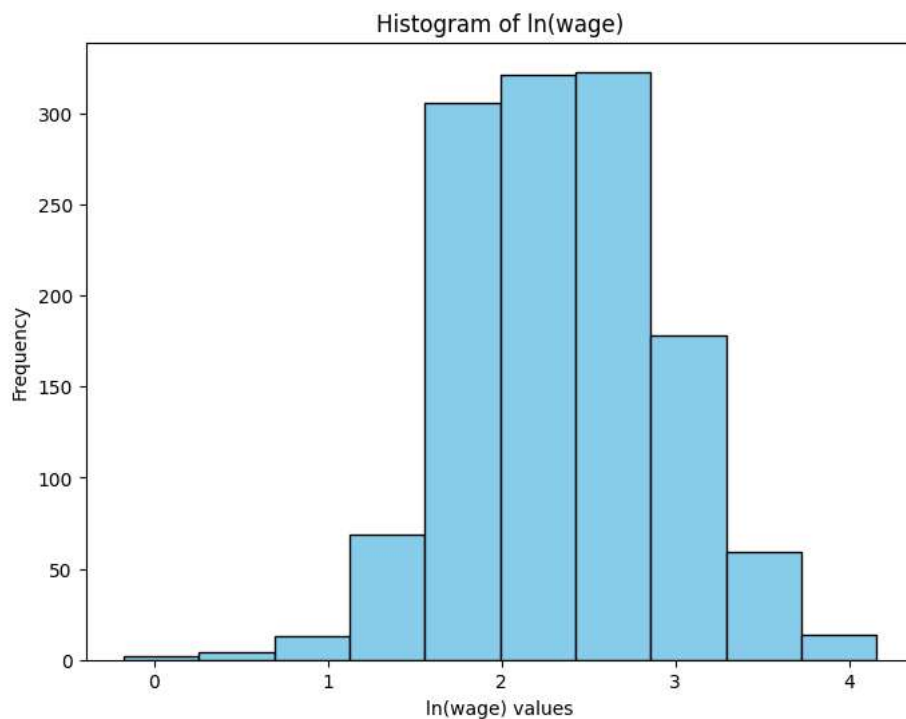
Distribution of weekly and non weekly wage earner



```
# Plot the histogram for the 'ln(wage)' column
plt.figure(figsize=(8, 6)) # Optional: Adjust figure size
plt.hist(df['ln(wage)'], bins=10, color='skyblue', edgecolor='black')

# Add titles and labels
plt.title('Histogram of ln(wage)')
plt.xlabel('ln(wage) values')
plt.ylabel('Frequency')

# Show the plot
plt.show()
```



```
Q1 = df['ln(wage)'].quantile(0.25)
Q3 = df['ln(wage)'].quantile(0.75)
IQR = Q3 - Q1
```

```
# Define outlier thresholds
lower_bound = Q1 - 1.5 * IQR
upper_bound = Q3 + 1.5 * IQR
```

```
# Identify outliers
outliers = df[(df['ln(wage)'] < lower_bound) | (df['ln(wage)'] > upper_bound)]
print(outliers)
```

```
↗
```

	w	fe	nw	un	ed	ex	age	wk	ln(wage)
97	2.000000	1.0	0.0	0.0	5.0	14.0	25.0	1.0	0.693147
372	0.840000	1.0	0.0	0.0	10.0	35.0	51.0	1.0	-0.174353
715	64.080002	1.0	0.0	0.0	16.0	12.0	34.0	1.0	4.160132
722	1.570000	0.0	1.0	0.0	16.0	6.0	28.0	1.0	0.451076
904	1.500000	1.0	0.0	0.0	14.0	17.0	37.0	0.0	0.405465
933	2.000000	0.0	0.0	0.0	11.0	1.0	18.0	0.0	0.693147
956	1.150000	0.0	0.0	0.0	12.0	43.0	61.0	1.0	0.139762
1256	1.670000	0.0	0.0	0.0	16.0	10.0	32.0	1.0	0.512824
1284	1.670000	1.0	0.0	0.0	10.0	45.0	61.0	1.0	0.512824

```
# Remove outliers
df_cleaned = df[(df['ln(wage)'] >= lower_bound) & (df['ln(wage)'] <= upper_bound)]
```

```
# Display the cleaned DataFrame
print(df_cleaned)
```

```
↗
```

	w	fe	nw	un	ed	ex	age	wk	ln(wage)
0	11.55	1.0	0.0	0.0	12.0	20.0	38.0	1.0	2.446686
1	5.00	0.0	0.0	0.0	9.0	9.0	24.0	0.0	1.609438
2	12.00	0.0	0.0	0.0	16.0	15.0	37.0	1.0	2.484907
3	7.00	0.0	1.0	1.0	14.0	38.0	58.0	0.0	1.945910
4	21.15	1.0	1.0	0.0	16.0	19.0	41.0	1.0	3.051640
...
1283	13.14	1.0	0.0	0.0	12.0	30.0	48.0	0.0	2.575661
1285	7.00	0.0	0.0	0.0	12.0	7.0	25.0	0.0	1.945910
1286	14.90	0.0	0.0	0.0	16.0	9.0	31.0	1.0	2.701361
1287	5.90	1.0	0.0	0.0	12.0	31.0	49.0	0.0	1.774952
1288	10.00	0.0	0.0	1.0	12.0	20.0	38.0	1.0	2.302585

```
[1280 rows x 9 columns]
```

```
df1 = df_cleaned
```

```
df1.columns
```

```
↗ Index(['w', 'fe', 'nw', 'un', 'ed', 'ex', 'age', 'wk', 'ln(wage)'], dtype='object')
```

```
X1=df1[['fe', 'nw', 'un', 'ed', 'ex', 'age', 'wk']]
```

```
X1.drop('age', axis=1, inplace=True)
```

```
↗ <ipython-input-126-ff48928db454>:1: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame
```

```
See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user\_guide/indexing.html#returning-a-view-versus-a-copy
X1.drop('age', axis=1, inplace=True)
```

```
Y=df1['ln(wage)']
```

```
X1.head()
```

```
↗
```

	fe	nw	un	ed	ex	wk
0	1.0	0.0	0.0	12.0	20.0	1.0
1	0.0	0.0	0.0	9.0	9.0	0.0
2	0.0	0.0	0.0	16.0	15.0	1.0
3	0.0	1.0	1.0	14.0	38.0	0.0
4	1.0	1.0	0.0	16.0	19.0	1.0

```
import statsmodels.api as sm
```

```
reg_result1 = sm.OLS(Y, sm.add_constant(X1)).fit()
```

```
print(reg_result1.summary())
```



OLS Regression Results

```
=====
Dep. Variable:          ln(wage)  R-squared:                0.408
Model:                  OLS       Adj. R-squared:            0.405
Method:                 Least Squares  F-statistic:              146.0
Date:                   Tue, 24 Sep 2024  Prob (F-statistic):      5.60e-141
Time:                   07:00:18   Log-Likelihood:           -750.43
No. Observations:       1280      AIC:                      1515.
Df Residuals:           1273      BIC:                      1551.
Df Model:                6
Covariance Type:        nonrobust
=====
```

	coef	std err	t	P> t	[0.025	0.975]
const	1.0743	0.070	15.281	0.000	0.936	1.212
fe	-0.2390	0.025	-9.721	0.000	-0.287	-0.191
nw	-0.1222	0.034	-3.568	0.000	-0.189	-0.055
un	0.1941	0.034	5.694	0.000	0.127	0.261
ed	0.0812	0.005	16.779	0.000	0.072	0.091
ex	0.0115	0.001	10.491	0.000	0.009	0.014
wk	0.2497	0.027	9.124	0.000	0.196	0.303

```
=====
Omnibus:                 24.780   Durbin-Watson:             1.976
Prob(Omnibus):            0.000   Jarque-Bera (JB):           41.698
Skew:                     -0.138   Prob(JB):                   8.82e-10
Kurtosis:                 3.840   Cond. No.                   146.
=====
```

Notes:

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

Start coding or [generate](#) with AI.

```
# Scatter plot of 'ln(wage)' vs 'ex'
plt.figure(figsize=(8, 6))
plt.scatter(df1['ex'], df1['ln(wage)'], color='skyblue', label='Data points')

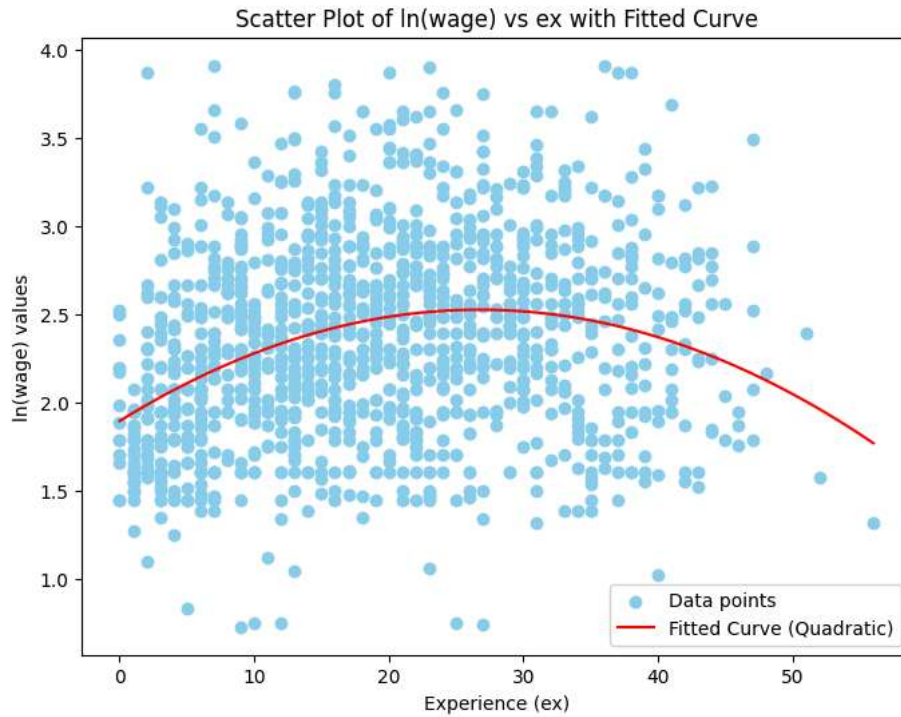
# Fit a second-degree polynomial (quadratic curve)
coefficients = np.polyfit(df1['ex'], df1['ln(wage)'], 2)
polynomial = np.poly1d(coefficients)

# Generate x values (ex range) for plotting the fitted curve
x_vals = np.linspace(df1['ex'].min(), df1['ex'].max(), 100)
y_vals = polynomial(x_vals)

# Plot the fitted curve
plt.plot(x_vals, y_vals, color='red', label='Fitted Curve (Quadratic)')

# Add titles and labels
plt.title('Scatter Plot of ln(wage) vs ex with Fitted Curve')
plt.xlabel('Experience (ex)')
plt.ylabel('ln(wage) values')
plt.legend()

# Show the plot
plt.show()
```



```
X2=X1
```

```
X2['ex^2'] = X2['ex']**2
```



<ipython-input-134-415623a447f6>:1: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
X2['ex^2'] = X2['ex']**2

```
X2.head()
```



	fe	nw	un	ed	ex	wk	ex^2
0	1.0	0.0	0.0	12.0	20.0	1.0	400.0
1	0.0	0.0	0.0	9.0	9.0	0.0	81.0
2	0.0	0.0	0.0	16.0	15.0	1.0	225.0
3	0.0	1.0	1.0	14.0	38.0	0.0	1444.0
4	1.0	1.0	0.0	16.0	19.0	1.0	361.0

```
reg_result2 = sm.OLS(Y, sm.add_constant(X2)).fit()
```

```
print(reg_result2.summary())
```



```

=====
                        OLS Regression Results
=====
Dep. Variable:          ln(wage)      R-squared:                0.427
Model:                  OLS           Adj. R-squared:           0.424
Method:                 Least Squares  F-statistic:              135.6
Date:                  Tue, 24 Sep 2024  Prob (F-statistic):      3.77e-149
Time:                  07:00:19        Log-Likelihood:           -728.83
No. Observations:      1280           AIC:                    1474.
Df Residuals:          1272           BIC:                    1515.
Df Model:              7
Covariance Type:       nonrobust
=====

```

	coef	std err	t	P> t	[0.025	0.975]
const	0.9621	0.071	13.510	0.000	0.822	1.102
fe	-0.2331	0.024	-9.633	0.000	-0.281	-0.186
nw	-0.1199	0.034	-3.560	0.000	-0.186	-0.054

```

un          0.1880    0.034    5.606    0.000    0.122    0.254
ed          0.0775    0.005   16.184    0.000    0.068    0.087
ex          0.0342    0.004    9.506    0.000    0.027    0.041
wk          0.2435    0.027    9.040    0.000    0.191    0.296
ex^2       -0.0005    8.23e-05   -6.608    0.000   -0.001   -0.000
=====
Omnibus:                34.727   Durbin-Watson:                1.978
Prob(Omnibus):          0.000   Jarque-Bera (JB):            68.010
Skew:                   -0.156   Prob(JB):                     1.71e-15
Kurtosis:               4.085   Cond. No.                     4.24e+03
=====

```

Notes:

[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
 [2] The condition number is large, 4.24e+03. This might indicate that there are strong multicollinearity or other numerical problems.

X3 = X2

```

X3['fe:nw'] = X3['fe']*X3['nw']
X3['fe:un'] = X2['fe']*X1['un']
X3['fe:ed'] = X2['fe']*X1['ed']
X3['fe:ex'] = X3['fe']*X1['ex']
X3['fe:wk'] = X3['fe']*X1['wk']

```

```

↳ <ipython-input-139-fb238cc67dde>:1: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

```

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
 X3['fe:nw'] = X3['fe']*X3['nw']

X1.head()

```

↳
   fe  nw  un  ed  ex  wk  ex^2  fe:nw  fe:un  fe:ed  fe:ex  fe:wk
0  1.0  0.0  0.0  12.0  20.0  1.0  400.0    0.0    0.0    12.0  20.0    1.0
1  0.0  0.0  0.0   9.0   9.0  0.0   81.0    0.0    0.0    0.0   0.0    0.0
2  0.0  0.0  0.0  16.0  15.0  1.0  225.0    0.0    0.0    0.0   0.0    0.0
3  0.0  1.0  1.0  14.0  38.0  0.0  1444.0    0.0    0.0    0.0   0.0    0.0
4  1.0  1.0  0.0  16.0  19.0  1.0   361.0    1.0    0.0   16.0  19.0    1.0

```

```
reg_result3 = sm.OLS(Y, sm.add_constant(X3)).fit()
```

```
print(reg_result3.summary())
```

```

↳
OLS Regression Results
=====
Dep. Variable:          ln(wage)    R-squared:                0.430
Model:                  OLS         Adj. R-squared:           0.425
Method:                 Least Squares   F-statistic:             79.65
Date:                  Tue, 24 Sep 2024   Prob (F-statistic):       2.89e-145
Time:                  07:00:19         Log-Likelihood:          -725.89
No. Observations:      1280            AIC:                    1478.
Df Residuals:          1267            BIC:                    1545.
Df Model:               12
Covariance Type:       nonrobust
=====
               coef      std err          t      P>|t|      [0.025      0.975]
-----
const          1.0023      0.095     10.508     0.000      0.815      1.189
fe           -0.3178      0.137     -2.322     0.020     -0.586     -0.049
nw           -0.1418      0.050     -2.835     0.005     -0.240     -0.044
un            0.1775      0.045      3.986     0.000      0.090      0.265
ed            0.0717      0.007     10.769     0.000      0.059      0.085
ex            0.0360      0.004      9.406     0.000      0.028      0.044
wk            0.2602      0.039      6.626     0.000      0.183      0.337
ex^2         -0.0005    8.27e-05   -6.568     0.000     -0.001     -0.000
fe:nw         0.0460      0.068      0.677     0.498     -0.087      0.179
fe:un         0.0171      0.068      0.251     0.802     -0.117      0.151
fe:ed         0.0116      0.010      1.206     0.228     -0.007      0.030
fe:ex        -0.0035      0.002     -1.609     0.108     -0.008      0.001
fe:wk        -0.0285      0.054     -0.527     0.598     -0.135      0.078
=====

```


Omnibus:35.547Durbin-Watson:1.972

Prob(Omnibus):0.000Jarque-Bera (JB):70.193

Skew:-0.159Prob(JB):5.73e-16

Kurtosis:4.102Cond. No.9.24e+03


=====

Notes:

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

[2] The condition number is large, 9.24e+03. This might indicate that there are strong multicollinearity or other numerical problems.


X2



	fe	nw	un	ed	ex	wk	ex^2	fe:nw	fe:un	fe:ed	fe:ex	fe:wk
0	1.0	0.0	0.0	12.0	20.0	1.0	400.0	0.0	0.0	12.0	20.0	1.0
1	0.0	0.0	0.0	9.0	9.0	0.0	81.0	0.0	0.0	0.0	0.0	0.0
2	0.0	0.0	0.0	16.0	15.0	1.0	225.0	0.0	0.0	0.0	0.0	0.0
3	0.0	1.0	1.0	14.0	38.0	0.0	1444.0	0.0	0.0	0.0	0.0	0.0
4	1.0	1.0	0.0	16.0	19.0	1.0	361.0	1.0	0.0	16.0	19.0	1.0
...
1283	1.0	0.0	0.0	12.0	30.0	0.0	900.0	0.0	0.0	12.0	30.0	0.0
1285	0.0	0.0	0.0	12.0	7.0	0.0	49.0	0.0	0.0	0.0	0.0	0.0
1286	0.0	0.0	0.0	16.0	9.0	1.0	81.0	0.0	0.0	0.0	0.0	0.0
1287	1.0	0.0	0.0	12.0	31.0	0.0	961.0	0.0	0.0	12.0	31.0	0.0
1288	0.0	0.0	1.0	12.0	20.0	1.0	400.0	0.0	0.0	0.0	0.0	0.0

1280 rows × 12 columns

X2.columns




Index(['fe', 'nw', 'un', 'ed', 'ex', 'wk', 'ex^2', 'fe:nw', 'fe:un', 'fe:ed', 'fe:ex', 'fe:wk'], dtype='object')

X4 = X2[['fe', 'nw', 'un', 'ed', 'ex', 'wk', 'ex^2']]

reg_result4 = sm.OLS(Y, sm.add_constant(X3)).fit()

print(reg_result4.summary())



OLS Regression Results											
=====											
Dep. Variable:	ln(wage)	R-squared:	0.430								
Model:	OLS	Adj. R-squared:	0.425								
Method:	Least Squares	F-statistic:	79.65								
Date:	Tue, 24 Sep 2024	Prob (F-statistic):	2.89e-145								
Time:	07:00:19	Log-Likelihood:	-725.89								
No. Observations:	1280	AIC:	1478.								
Df Residuals:	1267	BIC:	1545.								
Df Model:	12										
Covariance Type:	nonrobust										
=====											
	coef	std err	t	P> t	[0.025	0.975]					

const	1.0023	0.095	10.508	0.000	0.815	1.189					
fe	-0.3178	0.137	-2.322	0.020	-0.586	-0.049					
nw	-0.1418	0.050	-2.835	0.005	-0.240	-0.044					
un	0.1775	0.045	3.986	0.000	0.090	0.265					
ed	0.0717	0.007	10.769	0.000	0.059	0.085					
ex	0.0360	0.004	9.406	0.000	0.028	0.044					
wk	0.2602	0.039	6.626	0.000	0.183	0.337					
ex^2	-0.0005	8.27e-05	-6.568	0.000	-0.001	-0.000					
fe:nw	0.0460	0.068	0.677	0.498	-0.087	0.179					
fe:un	0.0171	0.068	0.251	0.802	-0.117	0.151					
fe:ed	0.0116	0.010	1.206	0.228	-0.007	0.030					
fe:ex	-0.0035	0.002	-1.609	0.108	-0.008	0.001					
fe:wk	-0.0285	0.054	-0.527	0.598	-0.135	0.078					
=====											
Omnibus:	35.547	Durbin-Watson:	1.972								
Prob(Omnibus):	0.000	Jarque-Bera (JB):	70.193								
Skew:	-0.159	Prob(JB):	5.73e-16								

Kurtosis: 4.102 Cond. No. 9.24e+03
 =====

Notes:

[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
 [2] The condition number is large, 9.24e+03. This might indicate that there are strong multicollinearity or other numerical problems.

Start coding or [generate](#) with AI.

```
plt.figure(figsize=(8, 6))
plt.scatter(df1['ed'], df1['ln(wage)'], color='skyblue', label='Data points')

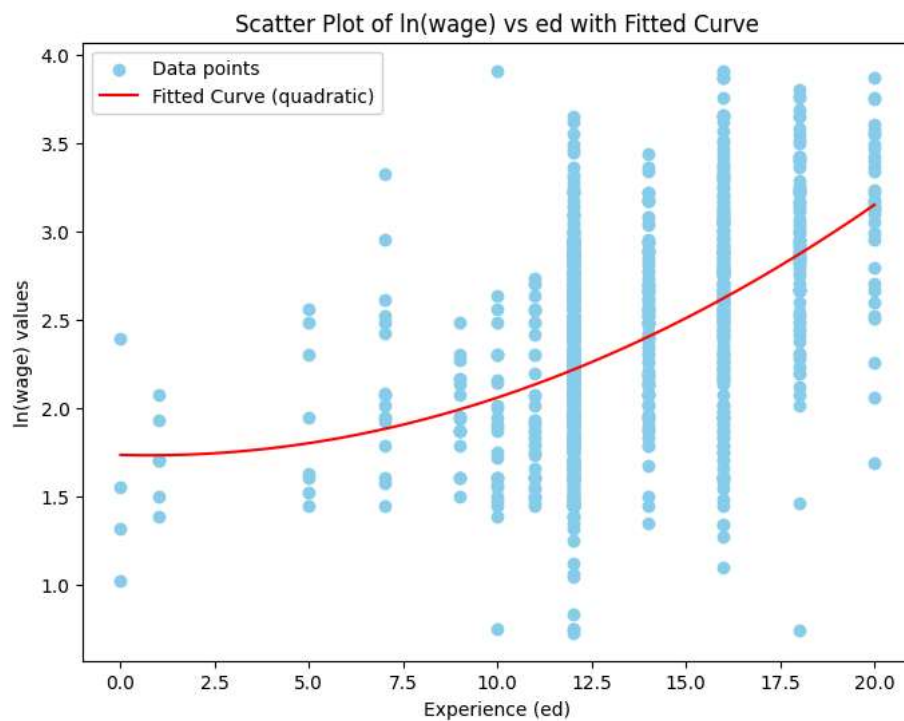
# Fit a second-degree polynomial (quadratic curve)
coefficients = np.polyfit(df1['ed'], df1['ln(wage)'], 2)
polynomial = np.poly1d(coefficients)

# Generate x values (ex range) for plotting the fitted curve
x_vals = np.linspace(df1['ed'].min(), df1['ed'].max(), 100)
y_vals = polynomial(x_vals)

# Plot the fitted curve
plt.plot(x_vals, y_vals, color='red', label='Fitted Curve (quadratic)')

# Add titles and labels
plt.title('Scatter Plot of ln(wage) vs ed with Fitted Curve')
plt.xlabel('Experience (ed)')
plt.ylabel('ln(wage) values')
plt.legend()

# Show the plot
plt.show()
```



X4.head()



	fe	nw	un	ed	ex	wk	ex^2
0	1.0	0.0	0.0	12.0	20.0	1.0	400.0
1	0.0	0.0	0.0	9.0	9.0	0.0	81.0
2	0.0	0.0	0.0	16.0	15.0	1.0	225.0
3	0.0	1.0	1.0	14.0	38.0	0.0	1444.0
4	1.0	1.0	0.0	16.0	19.0	1.0	361.0

```
X4['ed^2'] = X4['ed']**2
```

```
>ipython-input-149-ee1ac2b9299c>:1: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead
```

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy

```
X4['ed^2'] = X4['ed']**2
```

```
reg_result5 = sm.OLS(Y, sm.add_constant(X3)).fit()
print(reg_result5.summary())
```

```
OLS Regression Results
```

	coef	std err	t	P> t	[0.025	0.975]
Dep. Variable:	ln(wage)			R-squared:	0.430	
Model:	OLS			Adj. R-squared:	0.425	
Method:	Least Squares			F-statistic:	79.65	
Date:	Tue, 24 Sep 2024			Prob (F-statistic):	2.89e-145	
Time:	07:00:20			Log-Likelihood:	-725.89	
No. Observations:	1280			AIC:	1478.	
Df Residuals:	1267			BIC:	1545.	
Df Model:	12					
Covariance Type:	nonrobust					
	coef	std err	t	P> t	[0.025	0.975]
const	1.0023	0.095	10.508	0.000	0.815	1.189
fe	-0.3178	0.137	-2.322	0.020	-0.586	-0.049
nw	-0.1418	0.050	-2.835	0.005	-0.240	-0.044
un	0.1775	0.045	3.986	0.000	0.090	0.265
ed	0.0717	0.007	10.769	0.000	0.059	0.085
ex	0.0360	0.004	9.406	0.000	0.028	0.044
wk	0.2602	0.039	6.626	0.000	0.183	0.337
ex^2	-0.0005	8.27e-05	-6.568	0.000	-0.001	-0.000
fe:nw	0.0460	0.068	0.677	0.498	-0.087	0.179
fe:un	0.0171	0.068	0.251	0.802	-0.117	0.151
fe:ed	0.0116	0.010	1.206	0.228	-0.007	0.030
fe:ex	-0.0035	0.002	-1.609	0.108	-0.008	0.001
fe:wk	-0.0285	0.054	-0.527	0.598	-0.135	0.078
Omnibus:	35.547		Durbin-Watson:	1.972		
Prob(Omnibus):	0.000		Jarque-Bera (JB):	70.193		
Skew:	-0.159		Prob(JB):	5.73e-16		
Kurtosis:	4.102		Cond. No.	9.24e+03		

Notes:

[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
 [2] The condition number is large, 9.24e+03. This might indicate that there are strong multicollinearity or other numerical problems.

```
from statsmodels.stats.diagnostic import het_breuschpagan
```

```
# Predict the values and compute residuals
```

```
predicted_vals = reg_result5.fittedvalues
```

```
residuals = reg_result5.resid
```

```
# Breusch-Pagan Test
```

```
lm_test = het_breuschpagan(residuals, sm.add_constant(predicted_vals))
```

```
print('Breusch-Pagan p-value:', lm_test[1])
```

```
Breusch-Pagan p-value: 0.0001357136150874963
```

Breusch-Pagan Test:

- How it works: This statistical test assesses **heteroscedasticity** by testing if the residuals' variance is related to the independent variables. If the test is significant, it indicates heteroscedasticity.
- Interpretation: A low p-value (typically < 0.05) indicates the presence of heteroscedasticity.

```
from statsmodels.stats.outliers_influence import reset_ramsey
```

```
# Run the OLS regression
```

```
model = sm.OLS(df1['ln(wage)'], sm.add_constant(X4[['fe', 'nw', 'un', 'ed', 'ex', 'wk', 'ex^2', 'ed^2']])).fit()
```

```
# Perform the Ramsey RESET test
```

```
reset_test = reset_ramsey(model)
```

```
print('Ramsey RESET p-value:', reset_test)
```

```
➦ Ramsey RESET p-value: <F test: F=2.2719128983106884, p=0.05955964618806872, df_denom=1.27e+03, df_num=4>
```

OVB If the p-value is small (e.g., less than 0.05), there's evidence of omitted variables or a misspecified model.

```
model = sm.OLS(df1['ln(wage)'], sm.add_constant(X4[['fe', 'nw', 'un', 'ed', 'ex', 'wk', 'ex^2', 'ed^2']])).fit()
print(model.summary())
```

```
➦
```

OLS Regression Results						
Dep. Variable:	ln(wage)	R-squared:	0.431			
Model:	OLS	Adj. R-squared:	0.428			
Method:	Least Squares	F-statistic:	120.6			
Date:	Tue, 24 Sep 2024	Prob (F-statistic):	4.88e-150			
Time:	07:45:17	Log-Likelihood:	-724.23			
No. Observations:	1280	AIC:	1466.			
Df Residuals:	1271	BIC:	1513.			
Df Model:	8					
Covariance Type:	nonrobust					
	coef	std err	t	P> t	[0.025	0.975]
const	1.2848	0.128	10.032	0.000	1.034	1.536
fe	-0.2305	0.024	-9.549	0.000	-0.278	-0.183
nw	-0.1190	0.034	-3.544	0.000	-0.185	-0.053
un	0.1894	0.033	5.664	0.000	0.124	0.255
ed	0.0242	0.018	1.329	0.184	-0.012	0.060
ex	0.0347	0.004	9.658	0.000	0.028	0.042
wk	0.2320	0.027	8.557	0.000	0.179	0.285
ex^2	-0.0006	8.22e-05	-6.826	0.000	-0.001	-0.000
ed^2	0.0021	0.001	3.027	0.003	0.001	0.003
Omnibus:	38.729	Durbin-Watson:	1.977			
Prob(Omnibus):	0.000	Jarque-Bera (JB):	78.616			
Skew:	-0.172	Prob(JB):	8.49e-18			
Kurtosis:	4.164	Cond. No.	7.73e+03			

Notes:

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

[2] The condition number is large, 7.73e+03. This might indicate that there are strong multicollinearity or other numerical problems.

```
# Predict the values and compute residuals
```

```
predicted_vals = model.fittedvalues
```

```
residuals = model.resid
```

```
# Breusch-Pagan Test
```

```
lm_test = het_breuschpagan(residuals, sm.add_constant(predicted_vals))
```

```
print('Breusch-Pagan p-value:', lm_test[1])
```

```
➦ Breusch-Pagan p-value: 4.1651668328051035e-05
```

```
model2 = sm.OLS(df1['ln(wage)'], sm.add_constant(X4[['fe', 'nw', 'un', 'ex', 'wk', 'ex^2', 'ed^2']])).fit()
```

```
print(model2.summary())
```

```
➦
```

OLS Regression Results						
Dep. Variable:	ln(wage)	R-squared:	0.431			
Model:	OLS	Adj. R-squared:	0.428			
Method:	Least Squares	F-statistic:	137.5			
Date:	Tue, 24 Sep 2024	Prob (F-statistic):	9.64e-151			
Time:	07:45:34	Log-Likelihood:	-725.12			
No. Observations:	1280	AIC:	1466.			
Df Residuals:	1272	BIC:	1507.			
Df Model:	7					
Covariance Type:	nonrobust					
	coef	std err	t	P> t	[0.025	0.975]