



Statistical Methods and Data Analysis (EN.625.603)
Project 1

Project 1

Lead is toxic, particularly for young children, and for this reason government regulations severely restrict the amount of lead in our environment. But this was not always the case. In the early part of the 20th century, the underground water pipes in many US cities contained lead, and lead from these pipes leached into drinking water. In this exercise you will investigate the effect of these lead water pipes on infant mortality.

- (a) Compute the average infant mortality rate (Inf) for cities with lead pipes and for cities with non-lead pipes. Is there a statistically significant difference in the averages
- (b) The amount of lead leached from lead pipes depends on the chemistry of the water running through the pipes. The more acidic the water (that is, the lower the pH), the more lead is leached. Run a regression of Inf on $Lead$, pH , and the interaction term $Lead \times pH$.
 - i. The regression includes four coefficients (the intercept and the three coefficients multiplying the regressors). Explain what each coefficient measures.
 - ii. Plot the estimated regression function relating Inf to pH for $Lead = 0$ and $Lead = 1$. Describe the differences in the regression functions and relate these differences to the coefficients discussed in (i).
 - iii. Does $Lead$ have a statistically significant effect on infant mortality? Explain.
 - iv. Does the effect of $Lead$ on infant mortality depend on pH ? Is this dependence statistically significant?
 - v. What is the average value of pH in the sample? At this pH level, what is the estimated effect of $Lead$ on infant mortality? What is the standard deviation of pH ? Suppose that the pH level is one standard deviation lower than the average level of pH in the sample; what is the estimated effect of $Lead$ on infant mortality? What if pH is one standard deviation higher than the average value?
 - vi. Construct a 95% confidence interval for the effect of $Lead$ on infant mortality when $pH = 6.5$.
- (c) The analysis in (b) may suffer from omitted variable bias because it neglects factors that affect infant mortality and that might potentially be correlated with $Lead$ and pH . Investigate this concern, using the other variables in the data set.

Solution

- (a) Using Python with Pandas library, we have the following statistics with n, \bar{x}, s_x for lead and m, \bar{y}, s_y for non-lead.

$$\begin{aligned} n &= 55 & \bar{x} &= 0.3812 & s_x &= 0.1478 \\ m &= 117 & \bar{y} &= 0.4033 & s_y &= 0.1531 \end{aligned}$$

Test hypothesis is as follows:

$$H_0 : \mu_x = \mu_y$$

$$H_1 : \mu_x < \mu_y$$

The level of significance is $\alpha = 0.05$.

The degrees of freedom and critical value are as follows:

$$\begin{aligned} df &= n + m - 2 \\ &= 55 + 117 - 2 \\ &= 170 \end{aligned}$$

$$\begin{aligned} t_{\alpha, df} &= t_{0.05, 170} \\ &= 1.6539 \end{aligned}$$

The pooled standard deviation is as follows:

$$\begin{aligned} s_p &= \sqrt{\frac{(n-1)s_x^2 + (m-1)s_y^2}{n+m-2}} \\ &= \sqrt{\frac{(55-1)0.1478^2 + (117-1)0.1531^2}{170}} \\ &= 0.1514 \end{aligned}$$

The test statistic is as follows:

$$\begin{aligned} t &= \frac{\bar{x} - \bar{y}}{s_p \sqrt{\frac{1}{n} + \frac{1}{m}}} \\ &= \frac{0.3812 - 0.4033}{0.1514 \sqrt{\frac{1}{55} + \frac{1}{117}}} \\ &= -0.8923 \end{aligned}$$

Because $t = -0.8923 > -t_{\alpha, df} = -1.6539$, we fail to reject the null hypothesis.

(b) i. The coefficients were calculated using Python and Pandas are as follows

OLS Regression Results						
Dep. Variable:	infrate	R-squared:	0.272			
Model:	OLS	Adj. R-squared:	0.259			
Method:	Least Squares	F-statistic:	20.91			
Date:	Tue, 15 Aug 2023	Prob (F-statistic):	1.47e-11			
Time:	19:10:49	Log-Likelihood:	108.52			
No. Observations:	172	AIC:	-209.0			
Df Residuals:	168	BIC:	-196.5			
Df Model:	3					
Covariance Type:	nonrobust					
	coef	std err	t	P> t	[0.025	0.975]
const	0.9189	0.174	5.267	0.000	0.574	1.263
lead	0.4618	0.221	2.087	0.038	0.025	0.899
ph	-0.0752	0.024	-3.098	0.002	-0.123	-0.027
lead-ph	-0.0569	0.030	-1.871	0.063	-0.117	0.003
Omnibus:	4.916	Durbin-Watson:	1.946			
Prob(Omnibus):	0.086	Jarque-Bera (JB):	4.987			
Skew:	0.411	Prob(JB):	0.0826			
Kurtosis:	2.861	Cond. No.	252.			

The regression includes four coefficients (the intercept and the three coefficients multiplying the regressors).

$$\text{Inf} = \beta_0 + \beta_1 \text{Lead} + \beta_2 \text{pH} + \beta_3 \text{Lead} \times \text{pH}$$

$$\begin{aligned}\beta_0 &= 0.9189 \\ \beta_1 &= 0.4618 \\ \beta_2 &= -0.0752 \\ \beta_3 &= -0.0569\end{aligned}$$

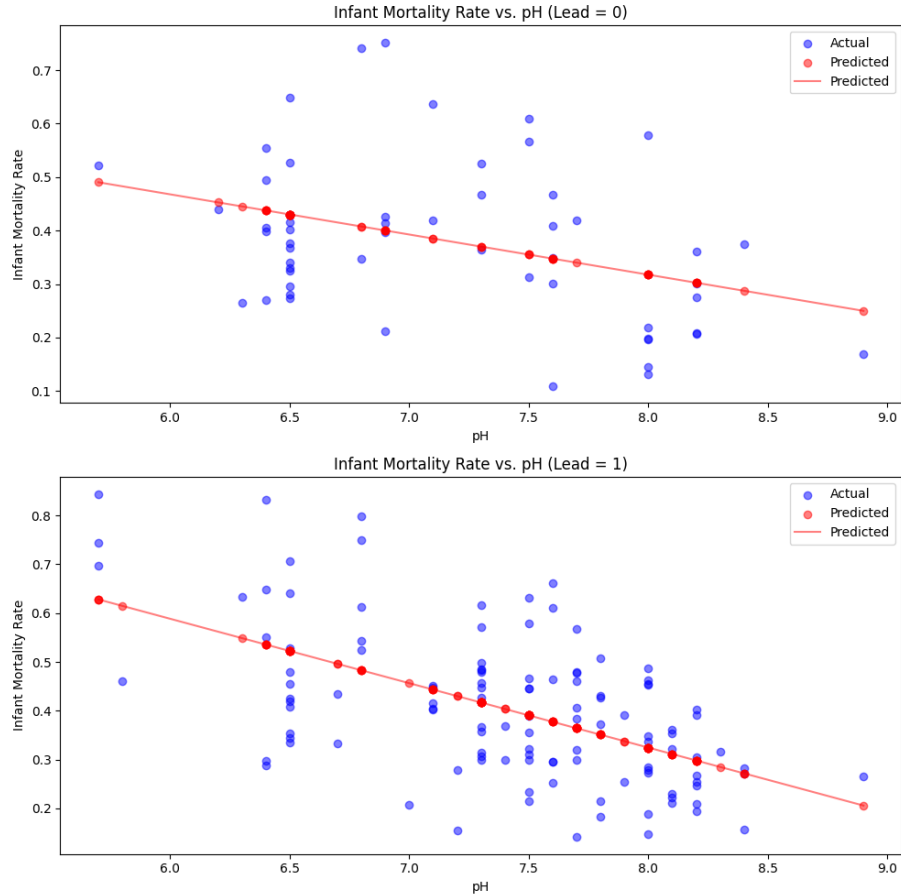
$\beta_0 = 0.9189$ is the average infant mortality when $Lead = 0$ and $pH = 0$.
 $\beta_1 = 0.4618$ is the effect of $Lead$ on infant mortality when $pH = 0$.
 $\beta_2 = -0.0752$ is the effect of pH on infant mortality when $Lead = 0$.
 $\beta_3 = -0.0569$ is the effect of pH on infant mortality when $Lead = 1$.

ii. The estimated regression function relating Inf to pH for $Lead = 0$ is as follows

$$\begin{aligned}Inf &= \beta_0 + \beta_2 pH + \epsilon \\ &= 0.9189 - 0.0752pH + \epsilon\end{aligned}$$

The estimated regression function relating Inf to pH for $Lead = 1$ is as follows

$$\begin{aligned}Inf &= \beta_0 + \beta_1 + \beta_2 pH + \beta_3 pH + \epsilon \\ &= 0.9189 + 0.4618 - 0.0752pH - 0.0569pH + \epsilon \\ &= 1.3807 - 0.1321pH + \epsilon\end{aligned}$$



- iii. To determine if Lead has a statistically significant effect on infant mortality, we use F -test from Python as follows

OLS Regression Results						
Dep. Variable:	infrate	R-squared:	0.234			
Model:	OLS	Adj. R-squared:	0.229			
Method:	Least Squares	F-statistic:	51.80			
Date:	Tue, 15 Aug 2023	Prob (F-statistic):	1.88e-11			
Time:	23:58:28	Log-Likelihood:	104.11			
No. Observations:	172	AIC:	-204.2			
Df Residuals:	170	BIC:	-197.9			
Df Model:	1					
Covariance Type:	nonrobust					
<hr/>						
	coef	std err	t	P> t	[0.025	0.975]
<hr/>						
const	1.1704	0.108	10.833	0.000	0.957	1.384
ph	-0.1057	0.015	-7.197	0.000	-0.135	-0.077
<hr/>						
Omnibus:	5.592	Durbin-Watson:	1.901			
Prob(Omnibus):	0.061	Jarque-Bera (JB):	5.729			
Skew:	0.427	Prob(JB):	0.0570			
Kurtosis:	2.738	Cond. No.	79.9			
<hr/>						

Notes:

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

F-statistic: 4.419053361850366

p-value: 0.01347744945676196

We have the following statistics

$$F = 4.4191$$

$$p - value = 0.0134$$

Thus, we can conclude that Lead has a statistically significant effect on infant mortality.

- iv. $p - value$ of the interaction $lead \times pH$ is 0.0631 which is greater than $\alpha = 0.05$. Thus, we can conclude that the effect of $Lead$ on infant mortality does not depend on pH .

OLS Regression Results						
Dep. Variable:	infrate		R-squared:	0.272		
Model:	OLS		Adj. R-squared:	0.259		
Method:	Least Squares		F-statistic:	20.91		
Date:	Wed, 16 Aug 2023		Prob (F-statistic):	1.47e-11		
Time:	01:04:58		Log-Likelihood:	108.52		
No. Observations:	172		AIC:	-209.0		
Df Residuals:	168		BIC:	-196.5		
Df Model:	3					
Covariance Type:	nonrobust					
	coef	std err	t	P> t	[0.025	0.975]
const	0.9189	0.174	5.267	0.000	0.574	1.263
lead	0.4618	0.221	2.087	0.038	0.025	0.899
ph	-0.0752	0.024	-3.098	0.002	-0.123	-0.027
lead-ph	-0.0569	0.030	-1.871	0.063	-0.117	0.003
Omnibus:	4.916		Durbin-Watson:	1.946		
Prob(Omnibus):	0.086		Jarque-Bera (JB):	4.987		
Skew:	0.411		Prob(JB):	0.0826		
Kurtosis:	2.861		Cond. No.	252.		
Notes:						
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.						
p-value for pH X lead: 0.0631						

- v. We have mean and standard deviation of pH as follows

$$\bar{pH} = 7.3227$$

$$s_{pH} = 0.6917$$

Average pH: 7.3227
Standard Deviation of pH: 0.6917
pH 1 Standard Deviation Above Average: 8.0144
pH 1 Standard Deviation Below Average: 6.6309

The estimated regression function relating Inf to pH for $Lead = 0$ is as follows

$$\begin{aligned} Inf &= \beta_0 + \beta_2 pH \\ &= 0.9189 - 0.0752(7.3227) \\ &= 0.3682 \end{aligned}$$

The estimated regression function relating Inf to pH for $Lead = 1$ is as follows

$$\begin{aligned} Inf &= \beta_0 + \beta_1 + \beta_2 pH + \beta_3 pH \\ &= 0.9189 + 0.4618 - 0.0752(7.3227) - 0.0569(7.3227) \\ &= 0.4134 \end{aligned}$$

Thus, the difference in the estimated infant mortality rates for $Lead = 0$ and $Lead = 1$ is

$$\begin{aligned} Inf_{Lead=0} - Inf_{Lead=1} &= 0.3682 - 0.4134 \\ &= -0.0452 \end{aligned}$$

pH one standard deviation above its mean is $7.3227 + 0.6917 = 8.0144$. The estimated regression function relating Inf to pH for $Lead = 0$ is as follows

$$\begin{aligned} Inf &= \beta_0 + \beta_2 pH \\ &= 0.9189 - 0.0752(8.0144) \\ &= 0.3162 \end{aligned}$$

The estimated regression function relating Inf to pH for $Lead = 1$ is as follows

$$\begin{aligned} Inf &= \beta_0 + \beta_1 + \beta_2 pH + \beta_3 pH \\ &= 0.9189 + 0.4618 - 0.0752(8.0144) - 0.0569(8.0144) \\ &= 0.3220 \end{aligned}$$

Thus, the difference in the estimated infant mortality rates for $Lead = 0$ and $Lead = 1$ is

$$\begin{aligned} Inf_{Lead=0} - Inf_{Lead=1} &= 0.3162 - 0.3220 \\ &= -0.0058 \end{aligned}$$

pH one standard deviation below its mean is $7.3227 - 0.6917 = 6.6310$. The estimated regression function relating Inf to pH for $Lead = 0$ is as follows

$$\begin{aligned} Inf &= \beta_0 + \beta_2 pH \\ &= 0.9189 - 0.0752(6.6310) \\ &= 0.4202 \end{aligned}$$

The estimated regression function relating Inf to pH for $Lead = 1$ is as follows

$$\begin{aligned} Inf &= \beta_0 + \beta_1 + \beta_2 pH + \beta_3 pH \\ &= 0.9189 + 0.4618 - 0.0752(6.6310) - 0.0569(6.6310) \\ &= 0.5047 \end{aligned}$$

Thus, the difference in the estimated infant mortality rates for $Lead = 0$ and $Lead = 1$ is

$$\begin{aligned}\text{Inf}_{Lead=0} - \text{Inf}_{Lead=1} &= 0.4202 - 0.5047 \\ &= -0.0844\end{aligned}$$

vi. The standard error of the estimated infant mortality rate is

$$s_{\text{Inf}} = 0.1513$$

The estimated mortality rate for $Lead = 0$ and $pH = 6.5$ is

$$\begin{aligned}\text{Inf} &= \beta_0 + \beta_2 pH \\ &= 0.9189 - 0.0752(6.5) \\ &= 0.4301\end{aligned}$$

The estimated mortality rate for $Lead = 1$ and $pH = 6.5$ is

$$\begin{aligned}\text{Inf} &= \beta_0 + \beta_1 + \beta_2 pH + \beta_3 pH \\ &= 0.9189 + 0.4618 - 0.0752(6.5) - 0.0569(6.5) \\ &= 0.5221\end{aligned}$$

Degrees of freedom and t-critical value for $\alpha = 0.05$ are as follows

$$\begin{aligned}n - p - 1 &= 172 - 3 - 1 \\ &= 168 \\ t_{\alpha/2, df} &= t_{0.025, 168} \\ &= 2.262\end{aligned}$$

The 95% confidence interval for the difference in the estimated infant mortality rates for $Lead = 0$ and $Lead = 1$ is

$$\begin{aligned}&= \text{Inf}_{Lead=0} - \text{Inf}_{Lead=1} \pm t_{\alpha/2, df} s_{\text{Inf}} \sqrt{\frac{1}{n_0} + \frac{1}{n_1}} \\ &= -0.0920 \pm 2.262(0.1513) \sqrt{\frac{1}{55} + \frac{1}{117}} \\ &= (-0.1480, -0.0360)\end{aligned}$$

(c) Of the 15 columns in the dataset, the analysis omitted the majority of other variables which might have an effect on infant mortality and correlated with $Lead$ and pH .

i. We can investigate water hardness index.

After adding *Hardness* to the model, and we can see that its p -value is 0.924, which is greater than 0.05. Thus, we can conclude that *Hardness* is not statistically significant in the model.

ii. We can investigate mom age index.

After adding *Age* to the model, and we can see that its p -value is 0.416, which is greater than 0.05. Thus, we can conclude that *Age* is not statistically significant in the model.

OLS Regression Results						
Dep. Variable:	infrate	R-squared:	0.295			
Model:	OLS	Adj. R-squared:	0.269			
Method:	Least Squares	F-statistic:	11.51			
Date:	Wed, 16 Aug 2023	Prob (F-statistic):	9.68e-11			
Time:	02:30:00	Log-Likelihood:	111.30			
No. Observations:	172	AIC:	-208.6			
Df Residuals:	165	BIC:	-186.6			
Df Model:	6					
Covariance Type:	nonrobust					
	coef	std err	t	P> t	[0.025	0.975]
const	0.9926	0.234	4.235	0.000	0.530	1.455
lead	0.2878	0.269	1.068	0.287	-0.244	0.820
ph	-0.0870	0.035	-2.502	0.013	-0.156	-0.018
hardness	-0.0002	0.002	-0.096	0.924	-0.004	0.004
lead-ph	-0.0264	0.040	-0.666	0.506	-0.105	0.052
lead-hardness	-0.0004	0.000	-1.206	0.230	-0.001	0.000
ph-hardness	4.252e-05	0.000	0.171	0.865	-0.000	0.001
Omnibus:	4.830	Durbin-Watson:	1.921			
Prob(Omnibus):	0.089	Jarque-Bera (JB):	4.851			
Skew:	0.409	Prob(JB):	0.0884			
Kurtosis:	2.903	Cond. No.	3.97e+04			

OLS Regression Results						
Dep. Variable:	infrate	R-squared:	0.278			
Model:	OLS	Adj. R-squared:	0.252			
Method:	Least Squares	F-statistic:	10.60			
Date:	Wed, 16 Aug 2023	Prob (F-statistic):	5.99e-10			
Time:	02:35:39	Log-Likelihood:	109.29			
No. Observations:	172	AIC:	-204.6			
Df Residuals:	165	BIC:	-182.5			
Df Model:	6					
Covariance Type:	nonrobust					
	coef	std err	t	P> t	[0.025	0.975]
const	1.5062	0.742	2.030	0.044	0.041	2.971
lead	0.4023	0.265	1.521	0.130	-0.120	0.925
ph	-0.1597	0.106	-1.513	0.132	-0.368	0.049
mom_rate	-2.8985	3.555	-0.815	0.416	-9.918	4.121
lead-ph	-0.0551	0.031	-1.803	0.073	-0.116	0.005
lead-mom_rate	0.2426	0.677	0.358	0.721	-1.095	1.580
ph-mom_rate	0.4176	0.507	0.823	0.412	-0.584	1.419
Omnibus:	4.682	Durbin-Watson:	1.975			
Prob(Omnibus):	0.096	Jarque-Bera (JB):	4.765			
Skew:	0.398	Prob(JB):	0.0923			
Kurtosis:	2.827	Cond. No.	3.44e+03			

```

1  # All code used to generate the results are shown below
2  import pandas as pd
3  import numpy as np
4  import statsmodels.api as sm
5  from scipy import stats
6  import scipy.stats
7  import matplotlib.pyplot as plt
8
9
10 class LeadMortalityDataframe:
11
12     df = None
13
14     column_name_year = None
15     column_name_city = None
16     column_name_state = None
17     column_name_age = None
18     column_name_hardness = None
19     column_name_ph = None
20     column_name_infrate = None
21     column_name_typhoid_rate = None
22     column_name_np_tub_rate = None
23     column_name_mom_rate = None
24     column_name_population = None
25     column_name_precipitation = None
26     column_name_temperature = None
27     column_name_lead = None
28     column_name_foreign_share = None
29
30     def __init__(self):
31         file_path = 'lead_mortality.xlsx'
32         file_sheet_name = 'Data'
33
34         self.df = pd.read_excel(file_path, sheet_name=file_sheet_name)
35         self.column_name_year = self.df.columns[0]
36         self.column_name_city = self.df.columns[1]
37         self.column_name_state = self.df.columns[2]
38         self.column_name_age = self.df.columns[3]
39         self.column_name_hardness = self.df.columns[4]
40         self.column_name_ph = self.df.columns[5]
41         self.column_name_infrate = self.df.columns[6]
42         self.column_name_typhoid_rate = self.df.columns[7]
43         self.column_name_np_tub_rate = self.df.columns[8]
44         self.column_name_mom_rate = self.df.columns[9]
45         self.column_name_population = self.df.columns[10]
46         self.column_name_precipitation = self.df.columns[11]
47         self.column_name_temperature = self.df.columns[12]
48         self.column_name_lead = self.df.columns[13]
49         self.column_name_foreign_share = self.df.columns[14]
50
51     def log_dataframe_info(self):
52         print(f'Number of rows: {self.df.shape[0]}')
53         print(f'Number of columns: {self.df.shape[1]}')
54         print('Column names:')
55         print(self.df.columns.tolist())
56         print('Data summary:')
57         print(self.df.describe(include='all'))
58
59     def get_lead_by_condition(self, condition):
60         return self.df[self.df[self.column_name_lead] == condition]
61

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```

62     def get_infrate_by_lead_condition(self, lead_condition):
63         df = self.get_lead_by_condition(lead_condition)
64         return df[self.column_name_infrate]
65
66
67 def part_a_solution():
68     lead_mortality = LeadMortalityDataframe()
69
70     infrate_lead_0 = lead_mortality.get_infrate_by_lead_condition(0)
71     infrate_lead_1 = lead_mortality.get_infrate_by_lead_condition(1)
72
73     n = infrate_lead_0.shape[0]
74     m = infrate_lead_1.shape[0]
75     avg_x = infrate_lead_0.mean()
76     avg_y = infrate_lead_1.mean()
77     std_x = infrate_lead_0.std()
78     std_y = infrate_lead_1.std()
79     level_of_significance = 0.05
80     d_freedom = n + m - 2
81     t_a_df = -scipy.stats.t.ppf(level_of_significance, d_freedom)
82     std_pooled = np.sqrt(
83         ((n - 1) * pow(std_x, 2) + (m - 1) * pow(std_y, 2)) / d_freedom)
84     t_statistics = (avg_x - avg_y) / (std_pooled * np.sqrt(1/n + 1/m))
85     print(f'n: {n}')
86     print(f'm: {m}')
87     print(f'avg_x: {avg_x:.4f}')
88     print(f'avg_y: {avg_y:.4f}')
89     print(f'std_x: {std_x:.4f}')
90     print(f'std_y: {std_y:.4f}')
91     print(f'std_pooled: {std_pooled:.4f}')
92     print(f't_a_df: {t_a_df:.4f}')
93     print(f't_statistics: {t_statistics:.4f}')
94
95
96 def part_b_i_solution():
97     lead_mortality = LeadMortalityDataframe()
98     lead_mortality.df["lead-pH"] = lead_mortality.df[lead_mortality.column_name_lead] *
99         \
100         lead_mortality.df[lead_mortality.column_name_ph]
101
102     x = sm.add_constant(lead_mortality.df[[lead_mortality.column_name_lead,
103         lead_mortality.column_name_ph, "lead-pH"]])
104     y = lead_mortality.df[lead_mortality.column_name_infrate]
105     model = sm.OLS(y, x)
106     results = model.fit()
107     print(results.summary())
108
109 def part_b_ii_solution():
110     lead_mortality = LeadMortalityDataframe()
111     lead_mortality.df["lead-pH"] = lead_mortality.df[lead_mortality.column_name_lead] *
112         \
113         lead_mortality.df[lead_mortality.column_name_ph]
114
115     x = sm.add_constant(lead_mortality.df[[lead_mortality.column_name_lead,
116         lead_mortality.column_name_ph, "lead-pH"]])
117     y = lead_mortality.df[lead_mortality.column_name_infrate]
118     model = sm.OLS(y, x)
119     results = model.fit()
120     fig, ax = plt.subplots(2, 1, figsize=(10, 10))

```

```

121 lead_mortality.df['pred_infrate'] = results.predict(x)
122
123 df_lead0 = lead_mortality.df[lead_mortality.df['lead'] == 0]
124 ax[0].scatter(df_lead0['ph'], df_lead0['infrate'],
125               color='blue', alpha=0.5, label='Actual')
126 sorted_df_lead0 = df_lead0.sort_values(by='ph')
127 ax[0].plot(sorted_df_lead0['ph'], sorted_df_lead0['pred_infrate'],
128            color='red', alpha=0.5, label='Predicted')
129 ax[0].set_title('Infant Mortality Rate vs. pH (Lead = 0)')
130 ax[0].set_xlabel('pH')
131 ax[0].set_ylabel('Infant Mortality Rate')
132 ax[0].legend()
133
134 df_lead1 = lead_mortality.df[lead_mortality.df['lead'] == 1]
135 ax[1].scatter(df_lead1['ph'], df_lead1['infrate'],
136               color='blue', alpha=0.5, label='Actual')
137 sorted_df_lead1 = df_lead1.sort_values(by='ph')
138 ax[1].plot(sorted_df_lead1['ph'], sorted_df_lead1['pred_infrate'],
139            color='red', alpha=0.5, label='Predicted')
140 ax[1].set_title('Infant Mortality Rate vs. pH (Lead = 1)')
141 ax[1].set_xlabel('pH')
142 ax[1].set_ylabel('Infant Mortality Rate')
143 ax[1].legend()
144
145 plt.tight_layout()
146 plt.show()
147
148
149 def part_b_iii_solution():
150     lead_mortality = LeadMortalityDataframe()
151     lead_mortality.df["lead-pH"] = lead_mortality.df[lead_mortality.column_name_lead] *
152                                     \
153                                     lead_mortality.df[lead_mortality.column_name_ph]
154     x = sm.add_constant(lead_mortality.df[[lead_mortality.column_name_lead,
155                                             lead_mortality.column_name_ph, "lead-pH"]])
156     y = lead_mortality.df[lead_mortality.column_name_infrate]
157     results = sm.OLS(y, x).fit()
158
159     x_ph = sm.add_constant(lead_mortality.df[[lead_mortality.column_name_ph]])
160     results_ph = sm.OLS(y, x_ph).fit()
161
162     f_test = results.compare_f_test(results_ph)
163     print(results_ph.summary())
164     print('F-statistic:', f_test[0])
165     print('p-value:', f_test[1])
166
167 def part_b_iv_solution():
168     lead_mortality = LeadMortalityDataframe()
169     lead_mortality.df["lead-pH"] = lead_mortality.df[lead_mortality.column_name_lead] *
170                                     \
171                                     lead_mortality.df[lead_mortality.column_name_ph]
172     x = sm.add_constant(lead_mortality.df[[lead_mortality.column_name_lead,
173                                             lead_mortality.column_name_ph, "lead-pH"]])
174     y = lead_mortality.df[lead_mortality.column_name_infrate]
175     results = sm.OLS(y, x).fit()
176     model = sm.OLS(y, x)
177     results = model.fit()
178     print(results.summary())
179     p_values_pHxLead = results.pvalues["lead-pH"]
180     print(f'p-value for pH X lead: {p_values_pHxLead:.4f}')

```

```

180
181
182 def part_b_v_solution():
183     lead_mortality = LeadMortalityDataframe()
184     avg_ph = lead_mortality.df[lead_mortality.column_name_ph].mean()
185     std_ph = lead_mortality.df[lead_mortality.column_name_ph].std()
186     ph_1_std_above = avg_ph + std_ph
187     ph_1_std_below = avg_ph - std_ph
188     print(f'Average pH: {avg_ph:.4f}')
189     print(f'Standard Deviation of pH: {std_ph:.4f}')
190     print(f'pH 1 Standard Deviation Above Average: {ph_1_std_above:.4f}')
191     print(f'pH 1 Standard Deviation Below Average: {ph_1_std_below:.4f}')
192
193
194 def part_b_vi_solution():
195     lead_mortality = LeadMortalityDataframe()
196     std_infrate = lead_mortality.df[lead_mortality.column_name_infrate].std()
197
198     print(f'Standard Deviation of Infant Mortality Rate: {std_infrate:.4f}')
199
200
201 def part_c_i_solution():
202     lead_mortality = LeadMortalityDataframe()
203     lead_mortality.df["lead-pH"] = lead_mortality.df[lead_mortality.column_name_lead] *
204         \
205         lead_mortality.df[lead_mortality.column_name_ph]
206     lead_mortality.df["lead-hardness"] = lead_mortality.df[lead_mortality.
207         column_name_lead] * \
208         lead_mortality.df[lead_mortality.column_name_hardness]
209     lead_mortality.df["ph-hardness"] = lead_mortality.df[lead_mortality.column_name_ph]
210         * \
211         lead_mortality.df[lead_mortality.column_name_hardness]
212
213     x = sm.add_constant(lead_mortality.df[[lead_mortality.column_name_lead,
214         lead_mortality.column_name_ph,
215         lead_mortality.column_name_hardness,
216         "lead-pH",
217         "lead-hardness",
218         "ph-hardness"]])
219     y = lead_mortality.df[lead_mortality.column_name_infrate]
220     model = sm.OLS(y, x)
221     results = model.fit()
222     print(results.summary())
223
224
225 def part_c_ii_solution():
226     lead_mortality = LeadMortalityDataframe()
227     lead_mortality.df["lead-pH"] = lead_mortality.df[lead_mortality.column_name_lead] *
228         \
229         lead_mortality.df[lead_mortality.column_name_ph]
230     lead_mortality.df["lead-mom_rate"] = lead_mortality.df[lead_mortality.
231         column_name_lead] * \
232         lead_mortality.df[lead_mortality.column_name_mom_rate]
233     lead_mortality.df["ph-mom_rate"] = lead_mortality.df[lead_mortality.column_name_ph]
234         * \
235         lead_mortality.df[lead_mortality.column_name_mom_rate]
236
237     x = sm.add_constant(lead_mortality.df[[lead_mortality.column_name_lead,
238         lead_mortality.column_name_ph,
239         lead_mortality.column_name_mom_rate,
240         "lead-pH",

```

```
235         "lead-mom_rate",
236         "ph-mom_rate"]])
237 y = lead_mortality.df[lead_mortality.column_name_infrate]
238 model = sm.OLS(y, x)
239 results = model.fit()
240 print(results.summary())
241
242
243 if __name__ == '__main__':
244     part_c_ii_solution()
```