ECON 0150 | Economic Data Analysis

The economist's data analysis workflow.

Part 4.3 | Categorical Predictors

General Linear Model

... a flexible approach to run many statistical tests.

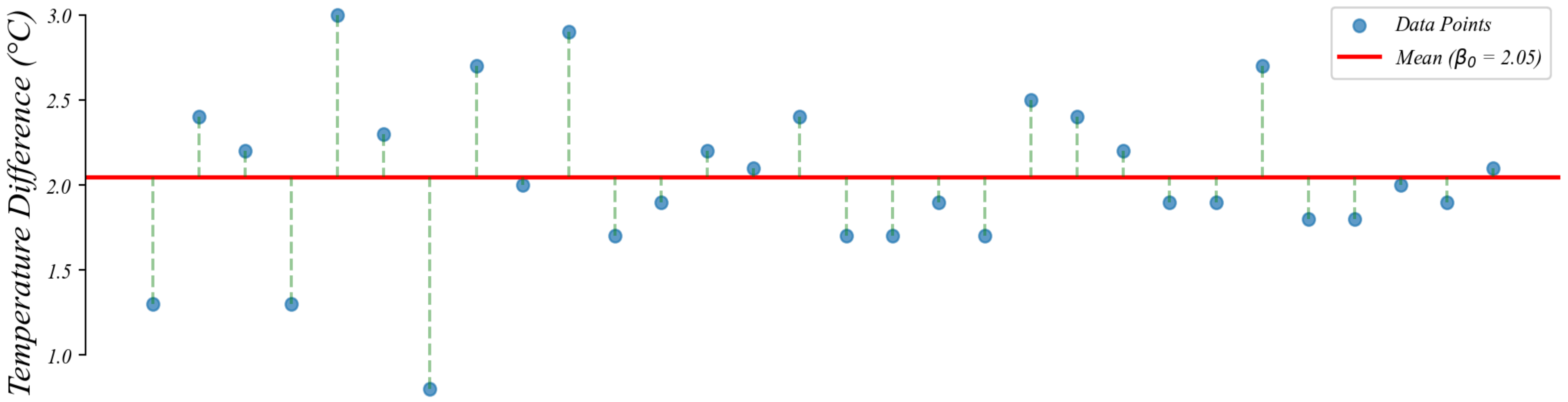
The Linear Model: $y_i = \beta_0 + \beta_1 x_i + \varepsilon_i$

- β_0 *is the intercept (value of $\bar{y}$ when $x = 0$)*
- β_1 *is the slope (change in y per unit change in x)*
- ε_i *is the error term (random noise around the model)*

OLS Estimation: Minimizes $\sum_{i=1}^{n} \varepsilon_i^2$

GLM: Intercept Model

A one-sample t-test is a horizontal line model.



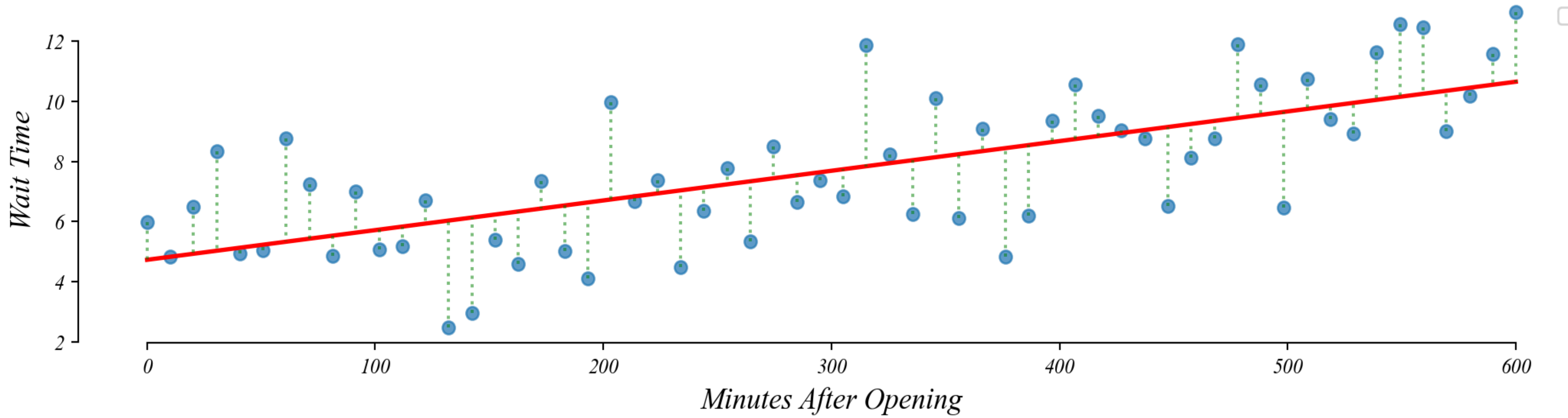
$$Temperature = \beta_0 + \varepsilon$$

> *the intercept β_0 is the estimated mean temperature*

> *the p-value is the probability of seeing β_0 if the null is true*

GLM: Intercept + Slope

A regression is a test of relationships.



$$\text{WaitTime} = \beta_0 + \beta_1 \text{MinutesAfterOpening} + \epsilon$$

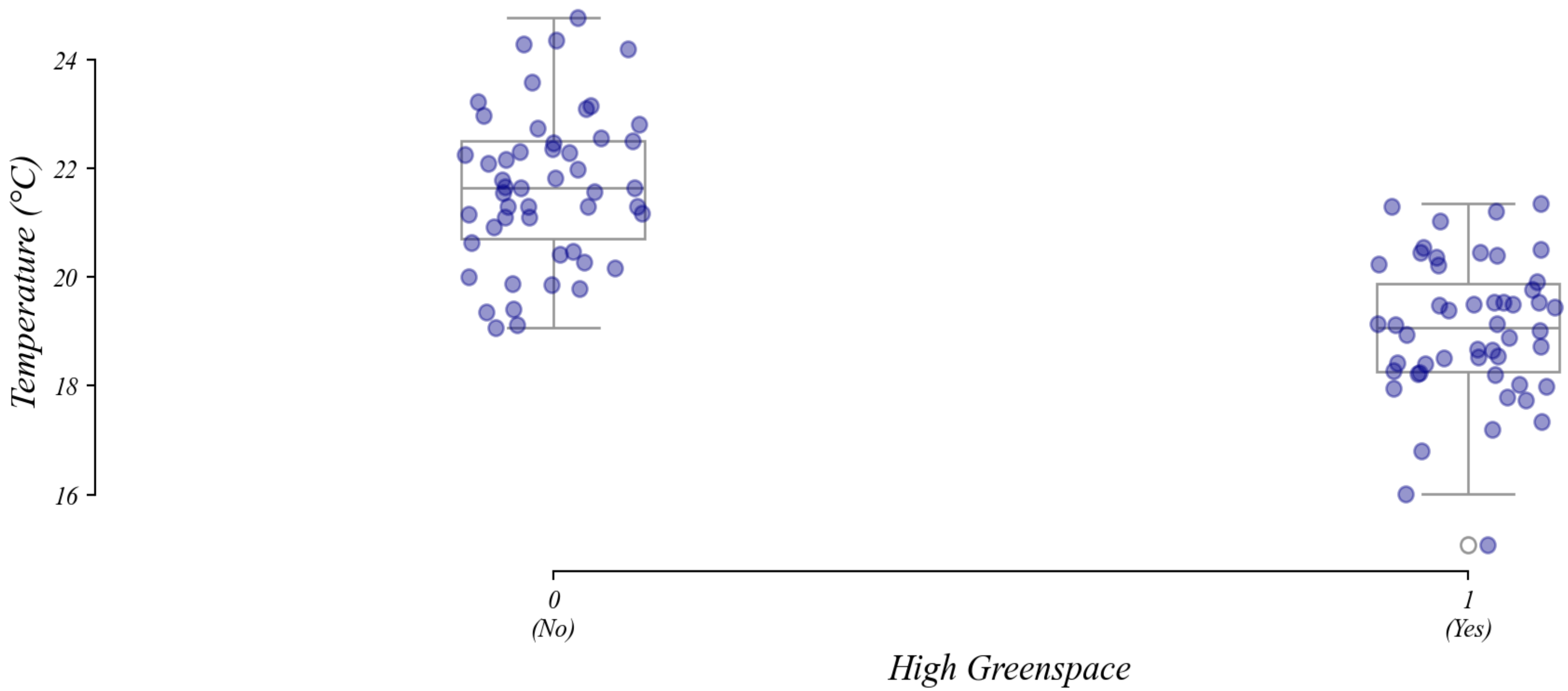
> *the intercept parameter β_0 is the estimated temperature at 0 on the horizontal*

> *the slope parameter β_1 is the estimated change in y for a 1 unit change in x*

> *the p-value is the probability of seeing parameter (β_0 or β_1) if the null is true*

GLM: City Greenspace and Temperature

Q. Is temperature lower in neighborhoods with more green space?



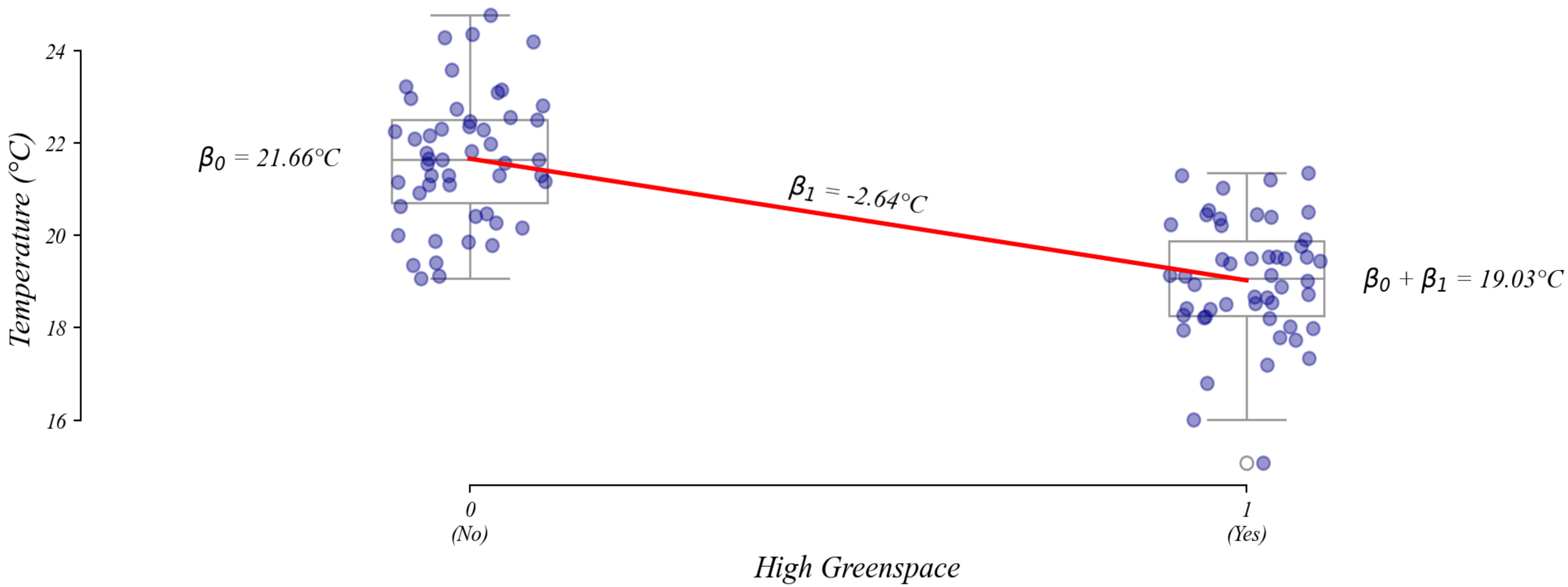
Q. Does temperature change as we move out on the horizontal axis?

$$Temperature = \beta_0 + \beta_1 \cdot HighGreen + \varepsilon$$

> the GLM performs a t-test on β_1, whether the difference is significant

GLM: City Greenspace and Temperature

Q. Does temperature change as we move out on the horizontal axis?



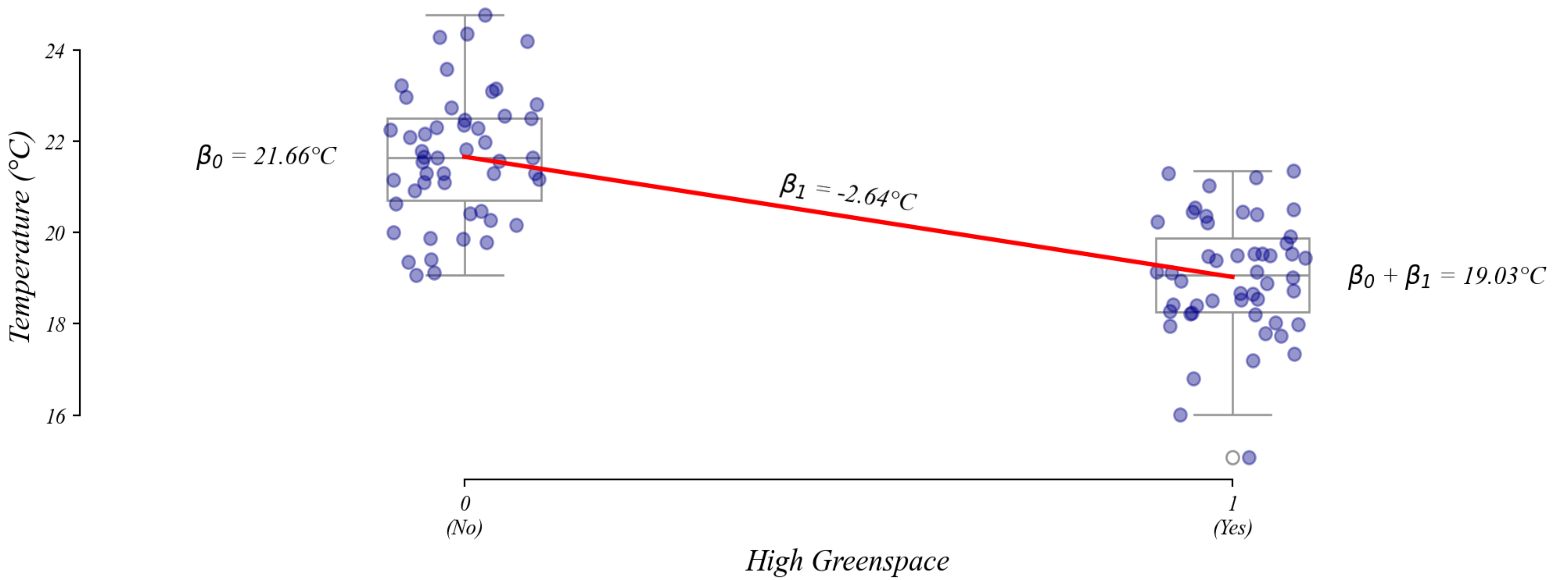
$$Temperature = \beta_0 + \beta_1 \cdot HighGreen + \varepsilon$$

How would we interpret β_0 here?

> *β_0 is the mean temperature in ($x = 0$) low green space cities (22.03°C)*

GLM: City Greenspace and Temperature

Q. Does temperature change as we move out on the horizontal axis?



$$Temperature = \beta_0 + \beta_1 \cdot HighGreen + \varepsilon$$

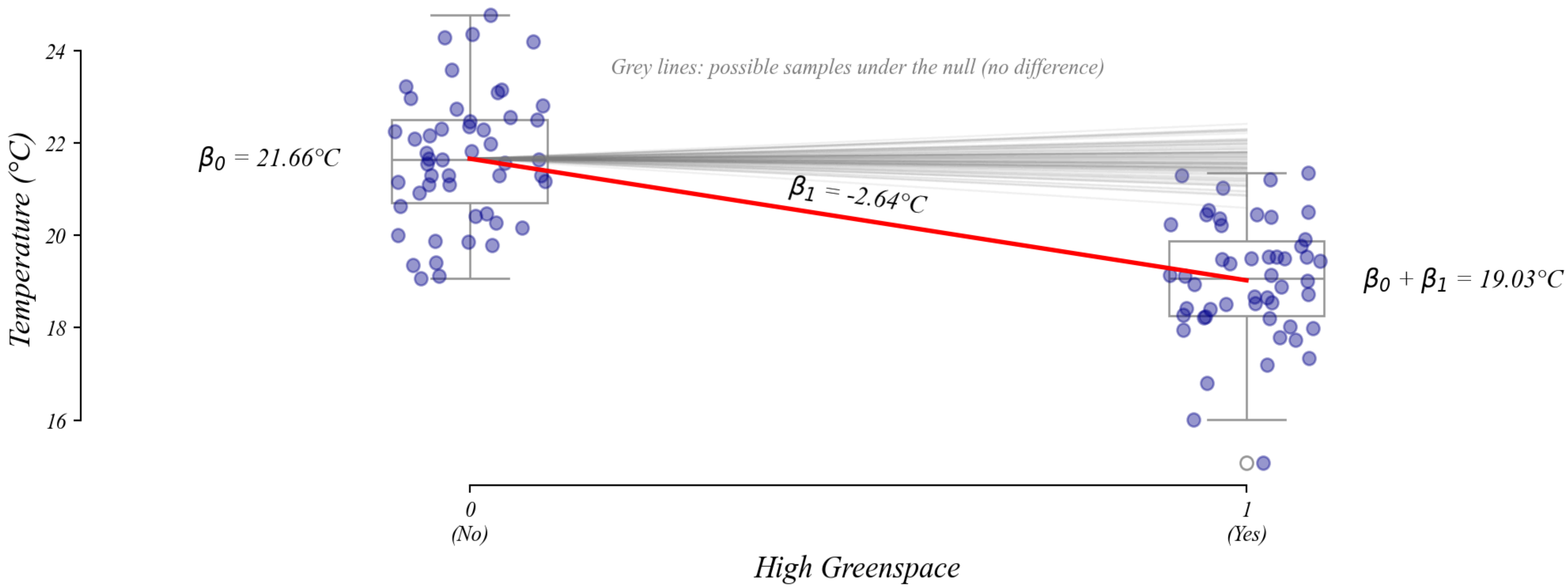
How would we interpret β_1 here?

> Cities with Green Space (x=1) have a temperature that is lower by β_1

> *ie. a one unit increase in* x *changes temperature by* β_1

GLM: City Greenspace and Temperature

Q. Does temperature change as we move out on the horizontal axis?



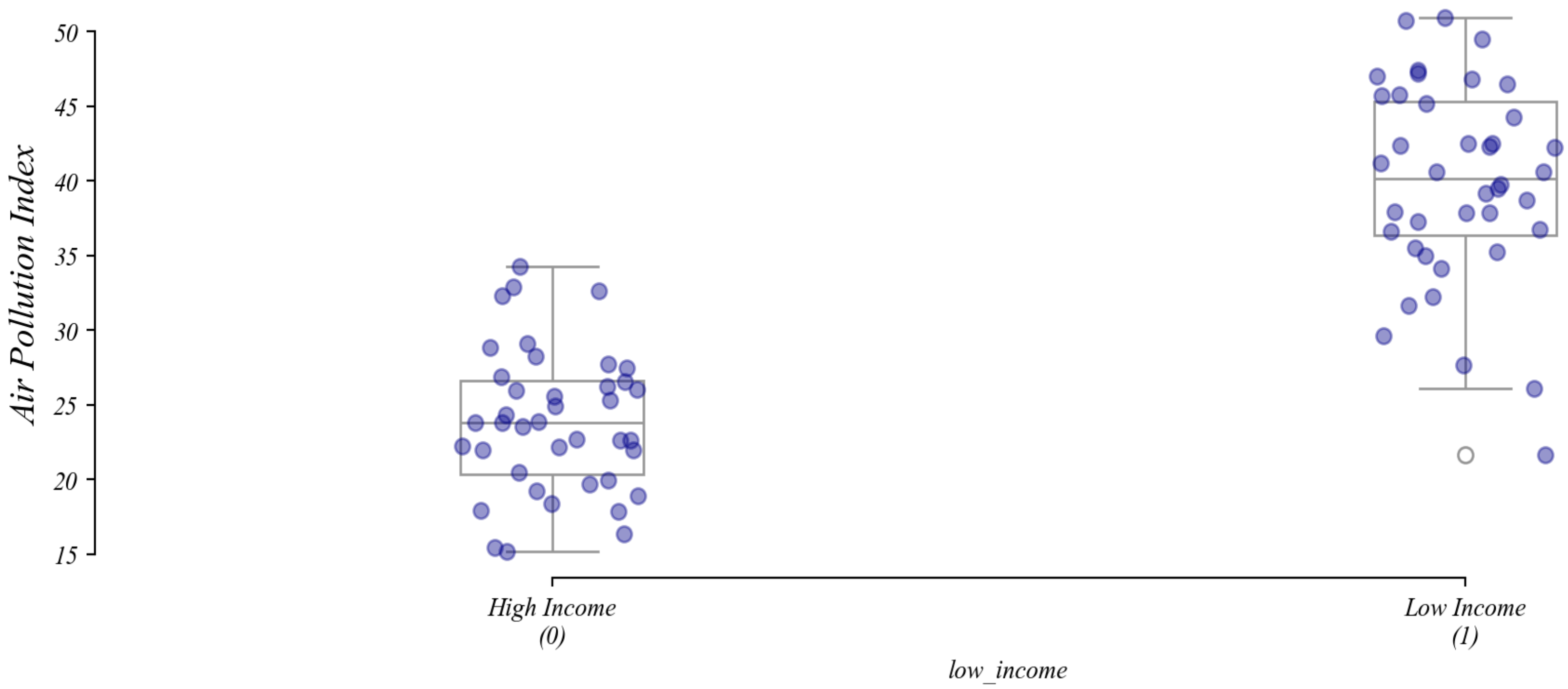
> *p-value on β_1: probability of a slope as extreme as β_1 under the null dist*

Exercise: Neighborhood Income and Pollution

Do low-income neighborhoods face higher pollution levels?

Step 1: Summarize the data

```
# Visualize Binary Predictor
sns.scatterplot(data, x='low_income', y='pollution')
plt.xticks([0,1], labels=['No', 'Yes'])
```



Exercise: Neighborhood Income and Pollution

Do low-income neighborhoods face higher pollution levels?

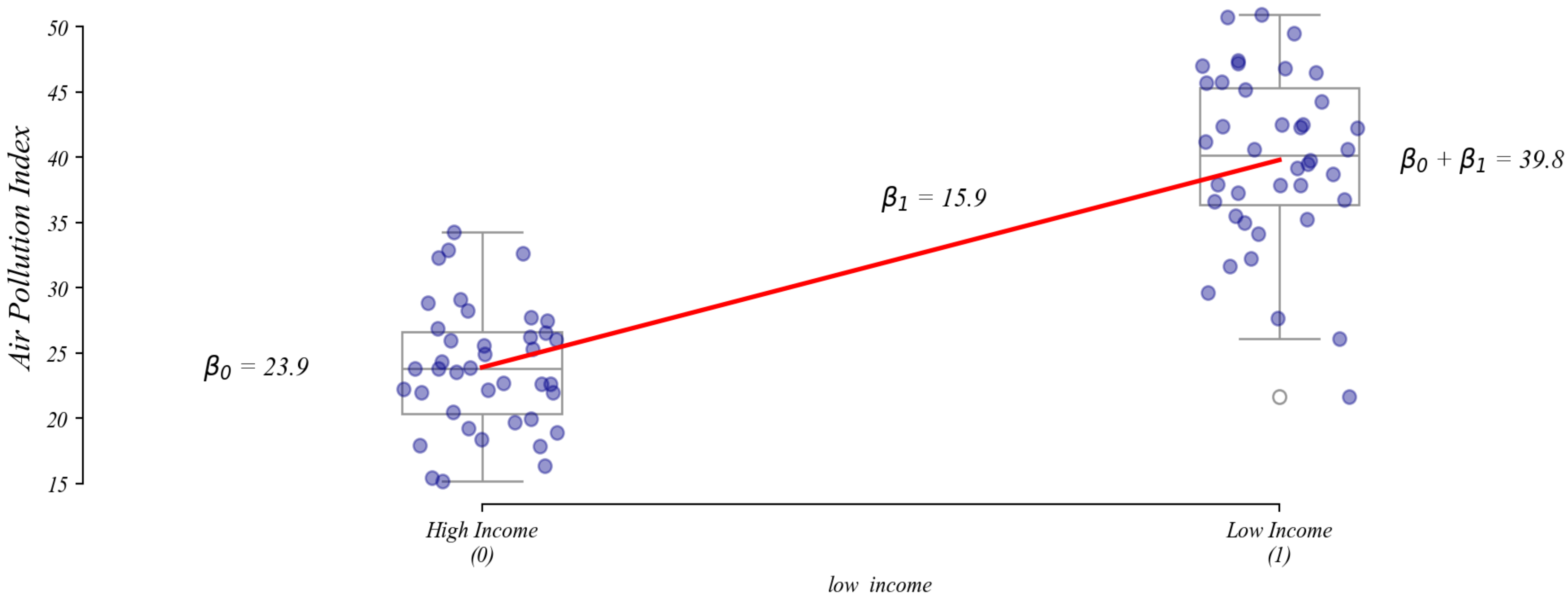
Step 2: Build a model

$$Pollution = \beta_0 + \beta_1 \cdot LowIncome + \varepsilon$$

Exercise: Neighborhood Income and Pollution

Do low-income neighborhoods face higher pollution levels?

Step 3: Estimate the model




```
# Model: y = b + mx
model = smf.ols('pollution ~ low_income', data).fit() # Intercept is included by default
print(model.summary().tables[1])
```

- β_0 = *Mean pollution in high-income areas (23.9)*
- β_1 = *Additional pollution in low-income areas (15.9)*

Exercise: Neighborhood Income and Pollution

Do low-income neighborhoods face higher pollution levels?

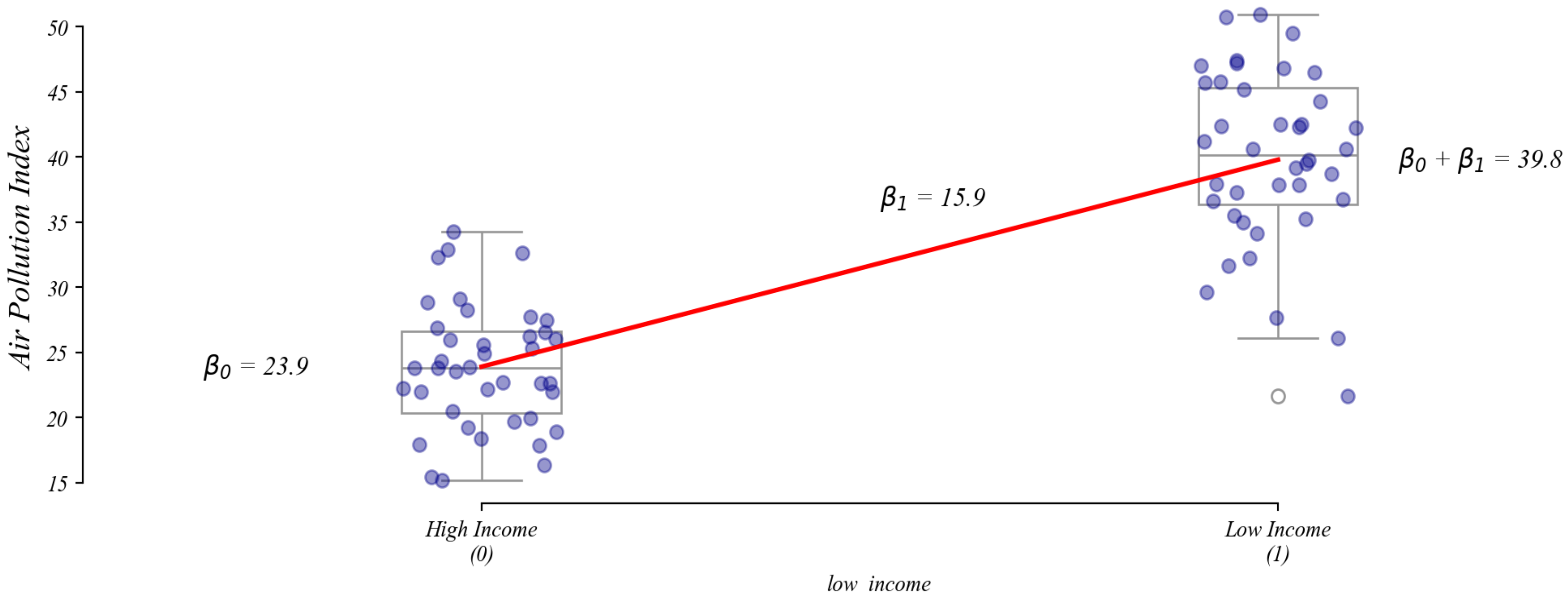
Step 4: Check the residuals

```
sns.scatterplot(x=model.predict(), y=model.resid, alpha=0.5)
plt.axhline(y=0, color='red', linestyle='-')
plt.xlabel('Fitted Values')
plt.ylabel('Residuals')
```

Exercise: Neighborhood Income and Pollution

Do low-income neighborhoods face higher pollution levels?

Step 5: Interpret and communicate the findings



> A significant positive β_1 suggests environmental quality differences between neighborhoods

GLM: Summary *(so far)*

GLM's unified framework for testing statistical models

One-Sample T-Test: Continuous outcome variable (y) with only an intercept

$$y = \beta_0 + \varepsilon$$

Relationships: Continuous outcome variable (y) with a continuous predictor (x)

$$y = \beta_0 + \beta_1 x + \varepsilon$$

Two-Sample T-Test: Continuous outcome variable (y) with a dummy ($Group$)

$$y = \beta_0 + \beta_1 \cdot Group + \varepsilon$$

Multiple Regression: Adding control variables to isolate relationships

> all use the same OLS framework and interpretation of coefficients and p-values