ECON 0150 | Economic Data Analysis

The economist's data analysis skillset.

Part 5.2 | Interaction Models

Model 3: Different Returns to Education

What if education benefits genders differently?

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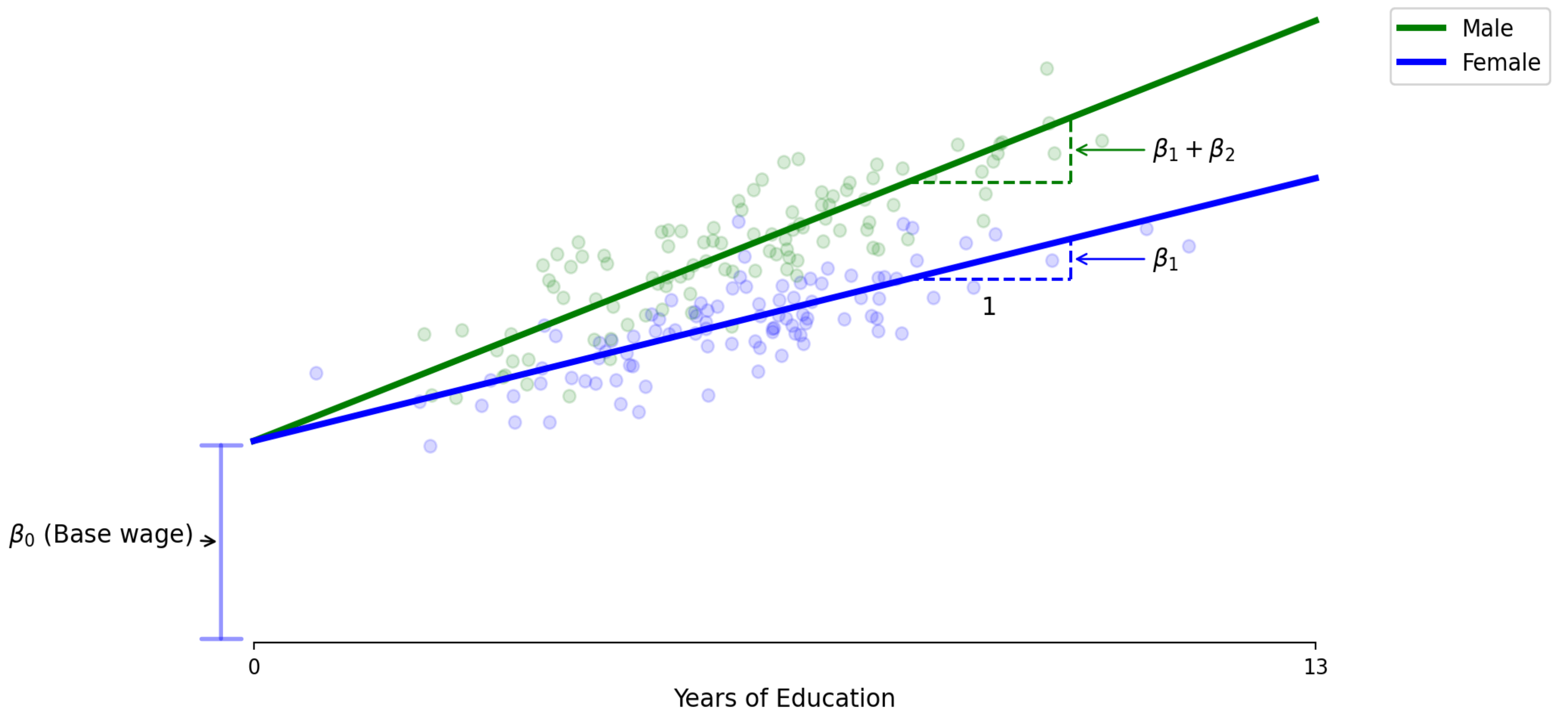


$$\text{Wage} = \beta_0 + \beta_1 \times \text{Education} + \beta_2 \times \text{Education} \times \text{Male} + \varepsilon$$

Model 3: Different Returns to Education

What if education benefits genders differently?

$$\text{Wage} = \beta_0 + \beta_1 \times \text{Education} + \beta_2 \times \text{Education} \times \text{Male} + \varepsilon$$

- *β_1 represents the female return to education.*
- *β_2 represents the additional male return to education (an additional slope)*
- *Male education effect is $\beta_1 + \beta_2$, creating diverging wage paths*

Model 3: The Code

Implementing the education-gender interaction model

```python
# Fit model with interaction between education and sex
model3 = smf.ols('LNINC ~ EDU + EDU:MALE', data=data).fit()
print(model3.summary().tables[1])
```

- *If* $\beta_2 > 0$ *and significant, male return to education is higher*
- *This model assumes same baseline (intercept) for both genders*

Why log income?

A $5,000 raise means different things to different people

- *If income is $25,000, that's a* ***20% raise***
- *If income is $200,000, that's a* ***2.5% raise***

Economists almost always use $\ln(\text{Income})$ *since it puts everyone on the same percentage scale.*

Interpreting Log Income

What does log do to our coefficients?

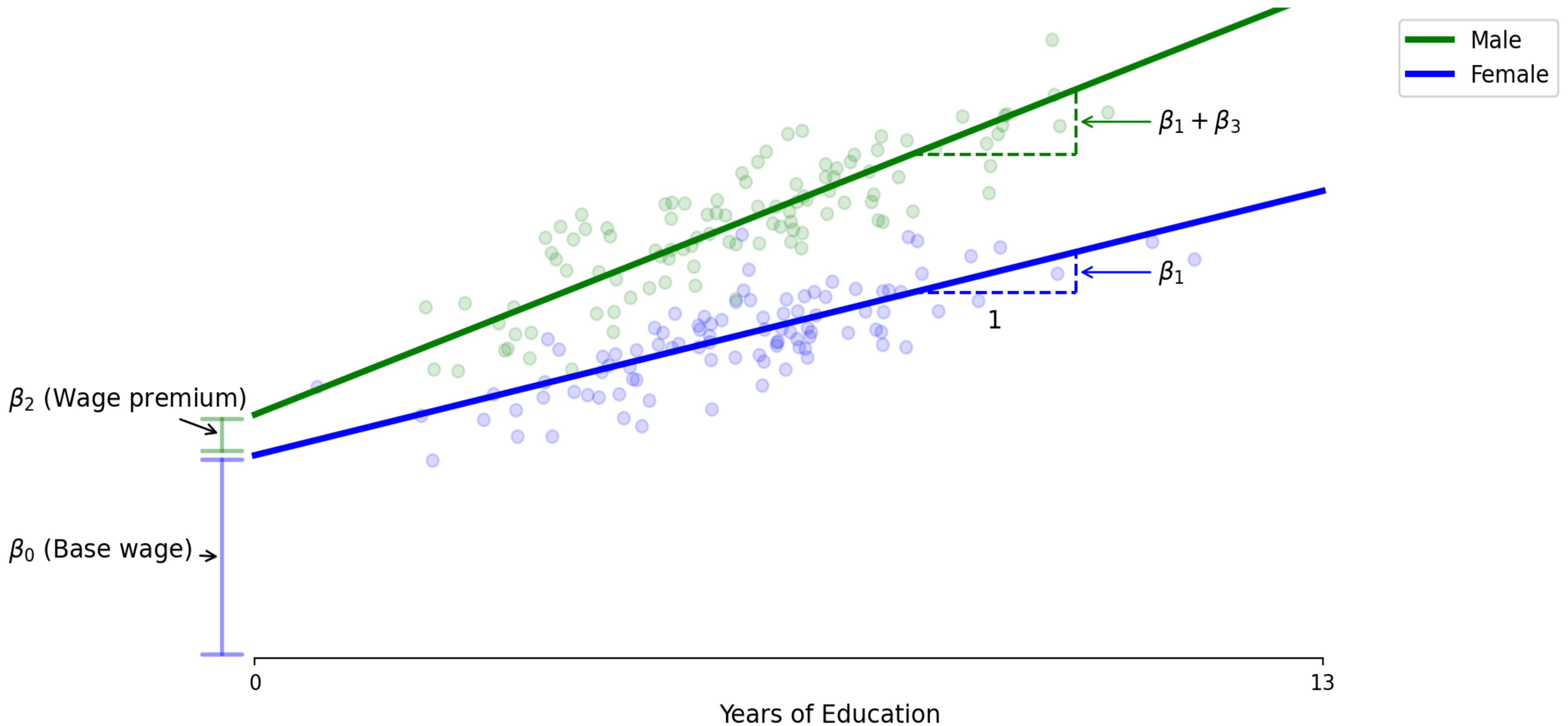
$$\ln(\text{Income}) = \beta_0 + \beta_1 \times \text{Education} + \beta_2 \times \text{Education} \times \text{Male} + \varepsilon$$

With $\ln(Y)$*, we interpret coefficients as* ***percent changes****.*

- *If* $\beta_1 = 0.08$*, income is* ***8% higher*** *with one more year of education.*
- *If* $\beta_2 = 0.03$*, men get an* ***additional 3%*** *per year of education.*

Model 4: Full Gender Difference Model

Combining fixed effects and interactions



$$\text{Wage} = \beta_0 + \beta_1 \times \text{Education} + \beta_2 \times \text{Male} + \beta_3 \times \text{Education} \times \text{Male} + \varepsilon$$

Model 4: Full Gender Difference Model

Combining fixed effects and interactions

$$\text{Wage} = \beta_0 + \beta_1 \times \text{Education} + \beta_2 \times \text{Male} + \beta_3 \times \text{Education} \times \text{Male} + \varepsilon$$

- β_0 = *base wage*
- β_2 = *initial wage gap (at zero education)*
- β_1 = *female returns to education*
- β_3 = *male education return premium*

Model 4: The Code

Implementing the full gender difference model

```
# Fit full model with both sex indicator and interaction
model4 = smf.ols('LNINC ~ EDU + MALE + EDU:MALE', data=data).fit()
print(model4.summary().tables[1])
```

> allows for differences in both baseline wages and educational returns

Comparison of Models

Different models answer different questions

Model 1: Fixed Effect

- *Question: "Is there a gender wage gap?"*

Model 2: Fixed Effect with Control

- *Question: "Is there a gender wage gap controling for education?"*

Model 3: Interaction Only

- *Question: "Are there differences in returns to education?"*

Model 4: Fixed Effect and Interaction

- *Question: "Does the gender wage gap vary with education level?"*

Key Takeaways

General linear model for analyzing group differences

Part 5.1 | Categorical Controls *('Fixed Effects')*

- *Captures level differences between groups*

Part 5.2 | Interactions

- *Capture differences in slopes*

Model Choice should be guided by your research question